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RESEARCH ARTICLE

Influential factors for mobile learning acceptance among Chinese users

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Abstract This study examines the factors that influence mobile learning adoption among Chinese university students. China's higher education market is large and mobile device ownership is considered a status symbol. Combined, these two factors suggest mobile learning could have a big impact in China. From the literature, we identified three major areas that may affect behavioral intention to adopt mobile learning in this context: pedagogical, personal, and social. A 27-item survey was administered online to 292 students at a northern Chinese university. Exploratory factor analysis was used to measure the reliability and validity of the survey items. Path analysis was then used to test the hypotheses in the proposed mobile learning acceptance model. Findings indicate that pedagogical factors have the greatest effect on students' behavioral intention to adopt mobile learning. Social influences, especially social image and subjective norm, also play a role. Personal innovativeness was not found to be a main factor, although it has some indirect influences.

Keywords China · Higher education · Mobile learning · Technology acceptance model · Pedagogical factors

Influential factors for mobile learning acceptance among Chinese users

Mobile devices, such as telephones, smartphones, and tablets, are constant companions for many people. The mobile industry has seen rapid growth in both developed and developing countries, with a high and steadily increasing rate of personal ownership (Deloitte 2013). Data access via mobile devices is predicted to be on a steady upward trajectory through 2018

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(Cisco 2014). In short, mobile communication technology has infiltrated everyday life on a global level.

The education market has viewed mobile devices, with their high levels of market penetration and continuously developing technological features, as a technology that is likely to influence learning (Koszalka and Ntloedibe-Kuswani 2010). Major educational platforms and content providers, such as Blackboard and Coursera, provide free apps for accessing courses and course material. Other apps abound, enabling mobile access of information and learning resources. Collectively, these conditions suggest that in the near future mobile devices will be heavily used to support learning in both formal and informal contexts. However, certain other conditions must be met in order for mobile devices to be effectively integrated into an educational setting such as a university.

Mobile learning currently is not required in typical public and private education contexts. Still, many learners use mobile devices to support their work in these settings, particularly for information access and communication (Gikas and Grant 2013). Device ownership appears to be a key barrier to formal integration in school settings. Unlike computers, phones and tablets are designed to be personal devices. For this reason, labs and lending programs may be impractical. A bring-your-own-device model seems likely to become the norm (Johnson et al. 2013), but is currently a problematic approach. Although device ownership is high, it is not at the ubiquitous level that Wong and Looi (2011) indicate is necessary for seamless mobile-assisted learning to occur. Further, differences in platforms and operating systems, as well as availability and stability of the wifi connections upon which many mobile Internet users are dependent (Deloitte 2013), can affect a student's ability to access mobile learning resources. For this reason, despite the presence of apps and mobile-accessible resources, mobile learning remains voluntary and is driven by end-users in most situations.

Being a mobile learner is not just about owning the appropriate device and having sufficient bandwidth. It also requires behavioral intention. In a higher education context, the learner must believe that using a mobile device will support learning and act accordingly. A student's behavioral intention to adopt mobile learning can be influenced by many factors. An educational institution may be able to provide support and in doing so influence elements of behavioral intention. However, other factors may include cultural environment and personal traits, which are more difficult to alter, but may be actively accommodated via the design and development of mobile applications and activities.

This study examines the factors that influence engagement in mobile learning among Chinese learners in a higher education setting. It extends Davis's (1989) technology acceptance model (TAM), which is a widely accepted model for explaining behavioral intention in the context of new technologies (Pedersen and Ling 2002). The study focuses on participants' current mobile learning activities, and investigates three aspects of influences on behavioral intention: pedagogical, social, and personal. Both macro (e.g., social influences and institutional learning environments) and micro (e.g., personal voluntariness) factors were explored.

Background

Mobile learning in tertiary education

Although mobile learning has been present in higher education for several years, it remains an emerging technology. As such, its contribution to higher education is still uncertain

(Veletsianos 2010), and faculty may need assistance in order to integrate mobile learning into their courses (Kukulska-Hulme 2012). Questions that are being explored by mobile learning scholars include:

- Will learners prefer mobile devices and perform better when using them versus a computer (Martin and Ertzberger 2013; Tossell et al. 2015; Wong et al. 2015).
- How is mobile learning best integrated into a learning context (Nguyen et al. 2015).
- Will mobile learning merely provide another point of information and communication access, or will a transformative pedagogy emerge (Dennen and Hao 2014aa; Sevillano-Garcia and Vazquez-Cano 2015).

When these questions are satisfactorily answered, mobile learning may no longer be considered an emerging technology, and will likely have assumed a stable position among other regularly used educational technologies.

Much of the scholarship on mobile learning thus far has focused on either application design or learning effectiveness (Wu et al. 2012), and has included a focus on models for designing and developing mobile learning solutions. For example, Koole's (2009) FRAME model suggests that mobile learning requires consideration of three elements—device, learner, and social—and how they interact with each other. Dennen and Hao's (2014a) framework demonstrates how mobile learning activities may be designed using traditional instructional systems design process models with special considerations of mobile affordances, limitations, and pedagogies during each design phase. Work done in this area is necessary to promote the development of pedagogically sound and usable mobile learning applications and experiences.

Increasingly, research has been conducted to examine student and instructor preferences and experiences. In a survey study, Abachi and Muhammad (2014) found that instructors and students had generally favorable views toward mobile learning. Cochrane and Bateman (2010) stressed the importance of using mobile devices to fluidly integrate Web 2.0 technologies into learning, which the students in Gikas and Grant's (2013) study indicate is readily happening. These students, as well as those in other studies (e.g., Gedik et al. 2012) share a favorable view of mobile learning, but readily acknowledge some of the related technology barriers and limitations. For example, students with lower socio-economic status, who may be the least likely to own current mobile devices, may have the most to gain from the information access provided by mobile devices (Kim et al. 2011). While these study findings suggest that many higher education institutions view mobile learning positively, they do not have clear implications for broader adoption.

Mobile learning in China

The potential mobile learning market in China is large. In 2011 China was predicted to be the second largest mobile education market, after the United States (GSMA 2011). The sheer size of China's population is a major reason for the large market size, although a 2013 study of developing countries positioned China as a leader among other countries for cell phone ownership (95 % of population); other developing countries with similar rates of ownership include Russia and Chile (Pew Research Center 2014). The same study showed that China was also among the leaders for smartphone ownership and mobile Internet access.

The formal introduction of mobile phone-based learning in China occurred in 2000, after which much progress was made (Fu and Yang 2009). For example, many of the mobile learning researchers included in Wu et al.'s (2012) meta-analysis of mobile learning studies are Chinese, particularly in the area of mobile learning app design. However, some of the issues to be addressed before mobile learning in China can be widespread and successful include the digital divide between urban and rural, poor areas and a teacher-centered curriculum (Yu et al. 2005). Other literature suggests that these barriers are gradually being overcome (Law et al. 2009; Nield 2004).

The conditions appear favorable for mobile learning to flourish in Chinese higher education. First, mobile device ownership is high in China, and especially among college students. Per the Pew Research Center (2014), 69 % of 18–29 year-olds in China and 83 % of college graduates were reported to own a smartphone. Additionally, national mobile infrastructure has been highly developed, with the number of Chinese mobile Internet users predicted to exceed PC Internet users in 2015 (iResearch Consulting Group. 2012). Currently, most first and second-tier Chinese universities have wireless Internet connections, which creates a positive environment for web-based mobile learning activities. At the same time, the dominant use of mobile devices remains entertainment oriented (iResearch Consulting Group 2012). However, the educational uses and preferences of Chinese learners, which will either enable or hinder the development of this learning market, have not been a primary focus of mobile learning research and is worthwhile examining. On the other hand, mobile learning has not yet been systematically implemented in Chinese universities. As a result, Chinese students have little formal guidance in this area.

Influential factors and hypotheses

The technology acceptance model (TAM; Davis 1989) has been used to predict behavioral intentions towards new technologies. A student's behavioral intention toward mobile learning represents readiness to adopt mobile learning activities (Davis 1989). TAM studies have been criticized for limitations that include reliance on self-report measures, and low validity (Lee et al. 2003). Over the years, various technology acceptance models have been proposed in efforts to expand on and refine TAM. These models added other personal and environmental moderating factors (e.g., TAM2, Venkatesh and Davis 2000; TAM3, Venkatesh and Bala 2008; and UTAUT, Venkatesh et al. 2003). However, there is empirical support for the robustness of the model, and studies have continued to show the predictive ability of TAM (e.g., King & He 2006; Marangunić and Granić 2015).

Some of the issues related to the utility of behavior intention studies include timing, specificity, and context. For example, some studies have been conducted after the new technology or system has been used. Thus, their findings may reflect continued-use behaviors more than the initial adoption intention (Lu et al. 2005). Further, the abstract nature of the TAM factors may result in findings that are not immediately useful to practitioners (Lee et al. 2003). Practitioners might be assisted by more concrete and robust definitions of influential factors. Finally, as the applied context shifts, so might the relative influence of different factors. For example, in an entertainment setting, perceived enjoyment is more important than perceived usefulness (van der Heijden 2004). In contrast, educational settings might find the opposite to the true.

In this study, we examine students' behavioral intentions toward mobile learning. We first conducted a literature review to identify the key influential factors for mobile learning and other learning technologies, such as wireless Internet services via mobile technology (Lu et al. 2005) and e-learning acceptance (Selim 2007). We then expanded the TAM model based on the results of our literature review, adding additional factors and categorizing them in three areas: pedagogical, social, and personal innovativeness. To make our model more concrete and relevant to practitioners, we modified the various pedagogical factors and developed survey items to reflect the mobile learning context. We did not focus on technological factors because technical limitations such as screen size do not affect learner adoption (Stockwell 2008) and the motivational factors related to using a new technology fade over time (Stead 2004; Stockwell 2008). Further, technological sophistication is not a direct measure of a technology's educational merits (Parsons and Ryu 2006). At the conclusion of this process, we generated 19 hypotheses related to our three factors.

Pedagogical hypotheses (Hypotheses 1–5)

Mobile learning is more than just accessing information otherwise accessible via computer on a portable device. Rather, mobile learning applications and activities require careful pedagogical design that reflects learning theory and meets the learner's needs (Dennen and Hao 2014aa). For example, Nokia developed a mobile learning platform, embedded into its phones, which includes English learning modules for Chinese owners (Liu et al. 2010). This platform and others like it are a response to the informal and formal learning interests of Chinese consumers, for whom English language skills are connected to degree and job advancements.

Within the pedagogical area, this study has five hypotheses, with one focused on perceived usefulness, one on ease of use, and three on facilitation.

In this study, perceived usefulness in the original model has been revised to *perceived usefulness of mobile learning content.* This factor indicates the degree to which a person believes that using mobile learning would enhance personal performance or learning outcomes (Davis 1989). The first hypothesis relates to perceived usefulness:

Hypothesis 1 The perceived usefulness of mobile learning content (PU) will positively affect participants' behavioral intention to adopt mobile learning (BI).

The TAM model (Davis 1989) and its successors (TAM2: Venkatesh and Davis 2000; UTAUT Venkatesh et al. 2003; and TAM3: Venkatesh and Bala 2008) indicate that perceived ease of use is a significant influential factor for new technology adoption. Ease of use focuses on the learner's ability to navigate and learn how to use a technology system, in this case a mobile learning one. When focused specifically on a mobile learning context, prior research is mixed. For example, Liu et al. (2010) study of mobile learning adoption factors in China, they found no significant effect of perceived ease of use on mobile learning adoption intention. They believed these results reflected the efforts of mobile manufacturers and learning content designers to create user-friendly systems. However, other studies (e.g., Cheon et al. 2012; Park et al. 2011) had findings consistent with earlier technology adoption research, showing that ease of use is a significant factor for predicting adoption. Believing that users are more likely to adopt a learning activity if the delivery system is easy to use, a second hypothesis was proposed:

Hypothesis 2 The perceived ease of use of mobile learning content (PE) will positively affect participants' behavioral intention to adopt mobile learning (BI).

One final pedagogical factor extracted from the literature is *perceived facilitating condition*, which indicates the availability of support that makes an act within the technology environment easier to accomplish (Thompson et al. 1991). The facilitating condition has been identified as an important factor that explains both behavioral intention and the actual behavioral action of adopting new technology (Venkatesh et al. 2003). In this study, we focus on a combination of system-based and human support that can help alleviate technical and learning challenges.

Facilitating condition, as synthesized from various TAM research, has been seen to be a determinant to positively influence perceived usefulness and perceived ease of use (Venkatesh and Bala 2008). For example, when assistance is available to students, the technology may seem easier to use. Additionally, facilitated learning experiences are likely to seem more relevant to learners, especially in the case of human facilitators who can communicate to learners why the learning activity or content should be valued.

We propose three hypotheses related to perceived facilitation:

Hypothesis 3 Perceived facilitation condition (PF) will positively affect participants' behavioral intention of adopting mobile learning (BI).

Hypothesis 4 Perceived facilitation condition (PF) will positively affect the perceived usefulness of mobile learning content (PU).

Hypothesis 5 Perceived facilitation condition (PF) will positively affect the perceived ease of use of mobile learning content (PE).

Social hypotheses (Hypotheses 6–13)

Mobile learners use telecommunications technology to manage both identity and relationships (Green et al. 2001). In this sense, they are not passive, but become social actors. They are influenced by their social groups, and they in turn may influence others.

Mobile devices do not just enable communication and information sharing. For many people, and especially in developing economies, mobile devices may function as a symbol of social progress (López-Nicolás et al. 2008). Park et al. (2007) studied the role of social influence in the context of Chinese attitudes toward mobile technology. They found that it had a positive role in adoption. In the Chinese context, mobile phone ownership is considered a marker of economic success and is considered socially desirable.

According to Karahanna and Straub (1999), social influence is comprised of three components, the subjective norm, image, and voluntariness. *Subjective norm* refers to an individual's perception of what others will think he should do (Fishbein and Ajzen 1975), and it has been found to positively influence student intention to adopt mobile learning (Cheon et al. 2012). In a general context, people might consider how people close to them, such as friends and family members, would perceive their mobile technology use. In the mobile learning context, the influence may come from people with a higher academic or social status, such as teachers and institutional authorities.

We hypothesized that the subjective norm will play a role in mobile learning adoption:

Hypothesis 6 Social subjective norm (Subnorm) will positively affect participants' behavioral intention of adopting mobile learning (BI).

Further, studies have shown that the subjective norm has a positive influential effect of on perceived usefulness (e.g., Lu et al. 2005; Venkatesh and Davis 2000), perceived facilitation condition (e.g., Venkatesh et al. 2003), and perceived ease of use (e.g., Lu et al. 2005). Thus, the following hypotheses were proposed:

Hypothesis 7 Social subjective norm (Subnorm) will positively affect the perceived usefulness of mobile learning content (PU).

Hypothesis 8 Social subjective norm (Subnorm) will positively affect perceived facilitation condition (PF).

Hypothesis 9 Social subjective norm (Subnorm) will positively affect the perceived ease of use of mobile learning content (PE).

Image in this context refers to the role technology plays in communicating social status (Moore and Benbasat 1991). In Karahanna and Straub's (1999) study, social image was not a significant influential factor for predicting people's attitudes toward adopting advanced technology. However, studies focusing on mobile phone adoption have yielded different results (Teo and Pok 2003). An early study found that 73 % of the executive class in big cities purchased mobile phones for both communication convenience and image purposes (Samson and Hornby 1998).

In China, mobile phone users are likely to be image conscious consumers. Mobile phones are expensive, and the cost of use has influenced who owns mobile phones and how and when people use them (Zhang and Prybutok 2005). People who own and use brand smartphones regularly can be assumed to have reached a certain economic status.

Prior studies have identified a positive relationship between image and perceived usefulness (Venkatesh and Bala 2008; Venkatesh and Davis 2000) and perceived ease of use of an innovation (Lu et al. 2005). Thus, we believe behavioral intention can be directly and indirectly influenced by social image.

Hypothesis 10 Social image (Image) will positively affect participants' behavioral intention of adopting mobile learning (BI).

Hypothesis 11 Social Image (Image) will positively affect the perceived usefulness of mobile learning content (PU).

Hypothesis 12 Social image (Image) will positively affect perceived ease of use of mobile learning content (PE).

Voluntariness represents the degree to which use of the mobile learning is perceived as a choice (Moore and Benbasat 1991). Voluntariness has been considered a moderating variable in Venkatesh and Bala's (2008) extended TAM model. However, in the learning context voluntariness may play a more direct role because learners may not always have a choice about whether or not to adopt a learning technology. When they are voluntary to try out mobile learning, they may expect more facilitation from others, especially from people with a higher academic status. In this sense, *Voluntariness* is included as a social influence that may affect perceived facilitation condition:

Hypothesis 13 Voluntariness (Volun) will positively affect perceived facilitation condition (PF).

Personal innovativeness hypotheses (Hypotheses 14–19)

Personal Innovativeness represents an individual's willingness to take a risk and try a new technology (Agarwal and Prasad 1998), in this case mobile learning. People adopt innovations at different rates, and these rates are related to personal comfort (Rogers 1995). People who are highly innovative are comfortably with new experiences and seek them out, not allowing themselves to be limited by not knowing the outcomes (Lu et al. 2005; Rogers 1995). Agarwal and Prasad (1998) further indicate that domain specific innovativeness may be a more powerful force than global innovativeness. Lu et al. (2005) found personal innovativeness to be a significant predictor of mobile learning preparedness in China. Essentially, people with a greater degree of personal innovativeness, particularly in the context of learning technologies, may be more likely than others to be early adopters or part of the early majority (Rogers 1995) for mobile learning. This may be particularly true in the absence of prior experiences with mobile learning, which has been identified as a barrier to integrating mobile devices in a teaching and learning context (Kukulska-Hulme and Pettit 2008). Further, personal innovativeness has shown to have direct positive impact on perceived usefulness and perceived ease of use of innovations (Lewis et al. 2003; Lu et al. 2005). Thus, three hypotheses were proposed accordingly.

Hypothesis 14 Personal innovativeness (Innov) will positively affect participants' behavioral intention of adopting mobile learning (BI).

Hypothesis 15 Personal Innovativeness (Innov) will positively affect perceived usefulness of mobile learning content (PU).

Hypothesis 16 Personal Innovativeness (Innov) will positively affect perceived ease of use of mobile learning content (PE).

Although the relationships between personal innovativeness and both behavioral intention and pedagogical factors are explored in the literature, little research has examined the relationship between personal innovativeness and social factors. However, innovativeness can be influenced by social factors, especially within the Chinese culture. For example, López-Nicolás et al. (2008) suggested that social reassurance will decrease personal uncertainty in trying out mobile technology and found that social influence have significant positive effects on personal attitudes towards mobile innovations. We propose that all three of these social factors will have a positive impact on personal innovativeness.

Hypothesis 17 Social image (Image) will positively affect personal innovativeness to try out mobile learning (Innov).

Hypothesis 18 Social subjective norm (Subnorm) will positively affect personal innovativeness to try out mobile learning (Innov).

Hypothesis 19 Voluntariness (Volun) will positively affect personal innovativeness to try out mobile learning (Innov).

Based on the above hypotheses, a research model for mobile learning adoption has been proposed (see Fig. 1). We anticipate the modified relationships can help explain factors that contribute to Chinese students' mobile learning intention. The next section we talk about how the instrument questionnaire were generated and distributed. The validity and reliability of instrument were first tested before we further test our hypotheses using the path analysis method.

Method

Participants

Data were collected from 292 undergraduate students at a Chinese university located in the northern part of the country. The in-state and out-state ratio of students in this university was about 2:3, with 35.2 % male and 64.8 % female students. The cell phone ownership

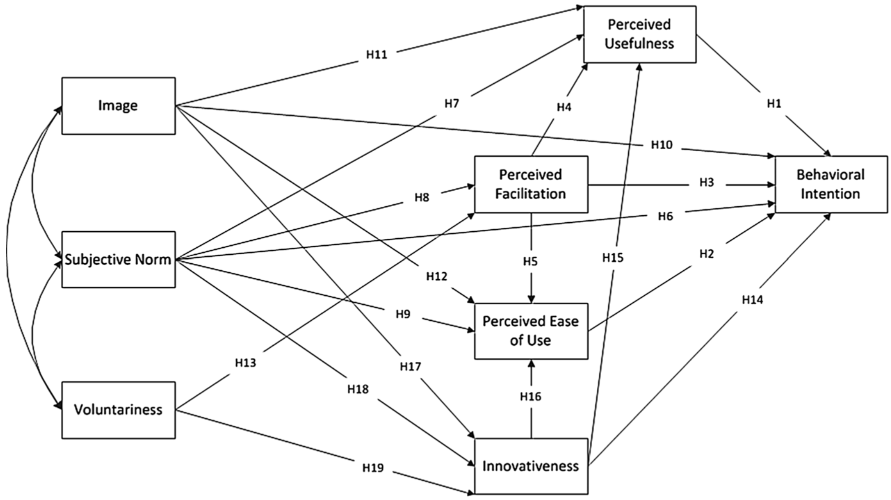

Fig. 1 Proposed model for mobile learning acceptance

Table 1 Demographic information of participants

Gender	Male	32 % (n = 92)
	Female	68 % (n = 198)
	Missing	1 % (n = 2)
Age	<18	0 % (n = 0)
	18–22	77 % (n = 224)
	23–30	19 % (n = 55)
	>30	0 % (n = 0)
	Missing	4 % (n = 13)
Grade	Freshman	20 % (n = 59)
	Sophomore	44 % (n = 128)
	Junior	24 % (n = 69)
	Senior	10 % (n = 29)
	Graduate	2 % (n = 6)
	Other (e.g. returning student, or teacher)	0 % (n = 1)
Type of mobile device	Regular phone (no internet capability)	4 % (n = 11)
	Regular phone (with internet capability)	45 % (n = 131)
	Smartphone	53 % (n = 156)
	iPad, Android pad, or tablets	4 % (n = 13)
	Personal digital assistant (e.g., Palm)	1 % (n = 2)

Note: Some students owned more than one mobile device, which is why the total number of mobile devices reported is larger than the sample size. Laptops were not considered mobile devices in this study among the students was 100 %. Moreover, this university provides Wi-Fi access in major on campus buildings and locations.

Participants ranged in age from 19 to 24. The female/male ratio was close to 3:1, which was a representative of the university's gender ratio. Surveys from ten participants were eliminated from the analysis because they were incomplete, leaving 282 valid data entries used for further research analysis. All participants owned a mobile device while 54 % of them own a smartphone, and 6 % own a tablet. Table 1 below presents more detailed demographic information of the participants.

Procedure and survey material

We used a two-step sampling technique to reach the maximum potential participants. First, snowball sampling was used to recruit participants. The snowball sampling method, proposed in social networking studies, helps gather additional respondents from the initial participants by asking them to share with their contacts (Goodman 1961). Specifically, we began by sending recruitment emails to student council executive committee members, who further contacted students in each of their colleges or departments. Second, when contacted, students voluntarily chose to participate in this study by completing an online survey. As a result, 292 students were recruited and participated in our study.

The participants were directed to an anonymous online survey. The survey instrument was a 30-item questionnaire developed from an extensive literature review, and then modified to fit the specific context of this study. Adaptation was minimal and focused on specifying mobile learning as the context for each item. There are 3–4 items per factor, and each item uses a 5-point Likert-type scale. The survey questions and the sources from which they were adapted are shown in Table 2.

Data analysis

To test our proposed hypotheses with modified survey items, we first used an exploratory factor analysis (EFA) to measure the instrument reliability and validity. Then, we conducted path analysis to test the proposed hypotheses in the mobile learning acceptance model.

EFA for instrument reliability and validity testing

EFA was used to measure the item reliability and validity. Eight factors were pre-determined to carry out the EFA analysis: behavioral intention (BI), perceived usefulness of mobile learning content (PU), perceived ease of use of mobile learning content (PE), perceived facilitating conditions (PF), image (Image), subjective norm (Subnrom), voluntariness (Volun), and personal innovativeness (Innov). Oblique rotation was requested to reorient the construct loading so that factors are represented in a less correlated way and are more interpretable. High factor loading on measured factors and low factor loading on other factors represent good convergent validity and discriminate validity. In order to increase the discriminate validity, five items (v10, v11, v17, v21, v24) were deleted from the survey scale because they correlated with factors in other constructs. Table 3 shows the final output of each item's validity, which indicates high factor loadings (>.70) for items in each of the eight constructs.

Table 2 Question items used in the study

Construct	Items	Source
Pedagogical factors		
Perceived Usefulness of mobile learning content (PU)	PU1—I think using mobile learning can increase the effectiveness of my academic performance	Lu et al. (2005), Park et al. (2011), Venkatesh and Davis (2000)
	PU2—I think using mobile learning can assist my studying	
	PU3—I think using mobile learning can enhance my performance in my courses	
Perceived ease of using of mobile learning content (PE)	PE1—mobile apps should be easy to navigate when working on learning tasks	López-Nicolás et al. (2008), Park et al. (2011), Saadé and Bahli (2005), Venkatesh and Davis (2000)
	PE2—it should be easy to learn how to use a new mobile learning application	
	PE3—it should be easy to be skillful at using a mobile learning application	
Perceived facilitating condition (PF)	PF1—I expect within-application instructional assistance (e.g., help or tutorials) to be available to me when I engage in mobile learning	Thompson et al. (1991), Venkatesh et al. (2003)
	PF2—guidance should be available to help select mobile learning applications	
	PF3—I expect to have specialized person(s) to provide assistance if I encounter learning difficulties in mobile learning	
	PF4—I expect to have specialized person(s) to provide assistance if I encounter technical difficulties in mobile learning	
Social factors		
Subjective norm (Subnorm)	Subnorm1—I am more likely to adopt mobile learning if my instructors encourage me to do so	López-Nicolás et al. (2008), Lu et al. (2005), Park et al. (2011), Venkatesh and Davis (2000)
	Subnorm2—I am more likely to adopt mobile learning if my family encourages me to do so	
	Subnorm3—I am more likely to adopt mobile learning if my peer group does	
	Subnorm4—I am more likely to adopt mobile learning if I see that the top students have	
Voluntariness (Volun)	Volun1—I would voluntarily engage in mobile learning	Venkatesh and Davis (2000)
	Volun2—instructors should not require students to use mobile resources	
	Volun3—although they might be helpful, mobile learning activities should not be compulsory	

Table 2 continued

Construct	Items	Source
Image (Image)	Image1—people who adopt mobile learning have more educational prestige than those who do not	Moore and Benbasat (1991)
	Image2—people who adopt mobile learning have a higher status in an education system	
	Image3—using a mobile device to support learning is a status symbol in my school	
	Image4—I will gain respect from my peers if I engage in mobile learning	
Personal factor		
Personal innovativeness (Innov)	Innov1—if affordable, I want my mobile device to be the model with the latest functions, services, and/or applications	López-Nicolás et al. (2008)
	Innov2—I would like to try out new or beta versions of mobile applications	
	Innov3—I want to be among the first people to try out new mobile functions, services and/or applications	
Behavioral intention		
Behavioral intention (BI)	BI1—I can benefit from mobile learning	López-Nicolás et al. (2008), Park et al. (2011), Wang et al. 2009), Venkatesh and Davis (2000)
	BI2—I predict I will use mobile learning in the future	
	BI3—I think others should use mobile learning as well	

Cronbach's alpha was used to test the instrument's reliability. As shown in Table 4, all constructs exhibit reliability values larger than the suggested cut-off value.70 (Hair et al. 2006). Both the validity and reliability results indicate that this newly formed instrument is sound for use with further statistical analysis.

Path analysis for hypotheses testing

Path analysis was used to test the proposed hypotheses in the mLearning acceptance model. This study used Mplus version 6.2 (Muthén and Muthén 1998–2016). Based on the descriptive statistics of the data and the cut-off values suggested by Finney and Distefano (2006), all skewness and kurtosis statistics were within ±2 and ±7 respectively. Therefore, the maximum likelihood (ML) estimation method was used with a sample size of 282 considering the continuous variables and their normal distributions. Because there is no single prescription for evaluating model fit, four common indices were used to examine the model-data fit: (1) Chi square statistics. A non-significant Chi square statistic indicates an adequate model fit. (2) Root mean square error of approximation (RMSEA): an RMSEA value equal or less than 0.06 or 0.08 indicates a good or fair model-data fit (Browne and Cudeck 1993). (3) Standardized root-mean-square residual (SRMR): a SRMR value that is smaller than 0.08 is recommended (Hu and Bentler 1999). (4) Comparative fit index (CFI)

Table 3 EFA result output for the survey item validity

	Component							
	Innov	Subnorm	Volun	Image	PU	PE	PF	BI
Exploratory factor analysis for the survey instrument validity								
V1	**.811**	.196	−.011	−.034	−.127	−.103	.161	−.070
V2	**.917**	−.168	.145	−.074	.079	−.014	−.103	.100
V3	**.727**	.037	−.128	.176	.018	.129	−.010	−.081
V7	.020	**.875**	−.104	−.059	.044	.055	.086	−.048
V8	−.090	**.980**	.087	.056	−.016	−.010	−.062	−.025
V9	.119	**.787**	.031	−.028	.052	.002	−.107	.114
V12	.045	−.092	**.941**	.061	.059	.077	−.025	−.077
V13	−.005	.177	**.772**	−.014	−.071	−.056	.106	.048
V14	−.069	.078	.086	**.915**	.001	−.025	.072	−.026
V15	−.001	.036	.044	**.939**	−.025	−.018	−.006	.022
V16	.073	−.140	−.072	**.849**	.068	.028	−.075	.065
V18	.029	.118	−.063	.064	**.705**	−.080	−.058	.195
V19	−.005	−.026	.049	−.098	**.878**	−.060	.011	.134
V20	−.030	.014	.001	.136	**.856**	.081	.127	−.192
V22	−.018	−.013	.033	−.049	.116	**.935**	−.059	−.019
V23	.005	.058	.010	.044	−.170	**.894**	.063	.086
V25	.009	.043	−.046	−.111	.173	.112	**.760**	−.002
V26	.006	−.029	.000	.057	−.007	−.044	**.984**	−.003
V27	.002	−.072	.075	.016	−.028	−.036	**.901**	.101
V28	.004	.005	.099	−.080	.168	.058	−.040	**.739**
V29	.004	−.062	−.033	−.010	−.059	.038	.112	**.911**
V30	−.026	.079	−.100	.171	−.024	−.025	.015	**.805**

Note: Items show in bold demonstrate high factor loadings (>.70). Items not shown in bold have markedly lower factor loadings (<.20)

with value that is greater than 0.90 or 0.95 is also preferable regarding the model-data fit (Hu and Bentler 1999).

Results

From our path analysis, we discovered that fifteen out of nineteen of hypotheses in the proposed model were supported with significant path coefficient values. Four hypotheses failed to achieve significant path coefficient sand were rejected. These rejected hypotheses were: H6 (Subnorm → BI), H9 (Subnorm → PE), H14 (Innov → BI), and H15 (Innov → PU). The paths and results of all proposed hypotheses are summarized in Table 5.

Figure 2 shows the final model. Significant paths are represented with bold lines while insignificant paths are represented with dotted lines. In the model, pedagogical factors contribute the most to students' behavioral intention to adopt mobile learning. Social and

Table 4 Item reliability with Cronbach's alpha

Factor	Item	Mean	SD	Cronbach's alpha
Innovativeness	Innov1	3.85	1.322	.785
	Innov2	3.57	1.247	
	Innov3	3.05	1.345	
Subjective Norm	Subnorm1	3.59	1.184	.891
	Subnorm2	3.61	1.115	
	Subnorm3	3.52	1.145	
Voluntariness	Volun1	4.04	1.142	.779
	Volun2	4.28	1.024	
Image	Image1	2.78	1.264	.899
	Image2	2.64	1.261	
	Image3	2.46	1.386	
Perceived Usefulness	PU1	3.25	1.173	.862
	PU2	3.55	1.053	
	PU3	3.38	1.097	
Perceived Ease of Use	PE1	3.44	1.140	.852
	PE2	3.43	1.121	
Perceived Facilitating Condition	PF1	3.92	1.130	.916
	PF2	4.00	1.084	
	PF3	4.02	1.075	
Behavioral Intention	BI1	3.58	1.146	.853
	BI2	3.54	1.113	
	BI3	3.30	1.156	

personal factors directly or indirectly affect students' behavior intention, and also positively affect students' personal innovativeness.

The model fit statistics suggest a fair to good model fit. Table 6 shows the fit indices both before and after the insignificant paths were deleted. The R-square estimates with insignificant paths deleted are shown in Table 7. Thus, the mLearning Intention Model, which had four insignificant paths deleted, was accepted due to its parsimonious structure compare to the proposed model.

Discussion

Overall, the results indicate that the seemingly ubiquitous nature of mobile communication technologies in non-learning context does not guarantee the acceptance of these technologies in the learning context (Levy and Kennedy 2005). The findings from the current study show that learners' choice in whether or not to engage in mobile learning activities are influenced by a combination of pedagogical, social, and personal innovativeness factors. Although personal innovativeness reflects an individual trait or preference, and as such is not swayed by the actions of others, both pedagogical and social factors might come into play when trying to influence mobile learning adoption. We further discuss each of the pedagogical, social, and personal factors below.

Table 5 Results of proposed hypotheses

	Hypothesis	Path	Result
H1	Perceived usefulness of mobile learning content (PU) will positively affect participants' behavioral intention of adopting mobile learning (BI)	PU → BI	Supported
H2	Perceived ease of use of mobile learning content (PE) will positively affect participants' behavioral intention of adopting mobile learning (BI)	PE → BI	Supported
H3	Perceived facilitation condition (PF) will positively affect participants' behavioral intention of adopting mobile learning (BI)	PF → BI	Supported
H4	Perceived facilitation condition (PF) will positively affect the perceived usefulness of mobile learning content (PU)	PF → PU	Supported
H5	Perceived facilitation condition (PF) will positively affect the perceived ease of use of mobile learning content (PE)	PF → PE	Supported
H6	Social subjective norm (Subnorm) will positively affect participants' behavioral intention of adopting mobile learning (BI)	Subnorm → BI	Rejected
H7	Social subjective norm (Subnorm) will positively affect the perceived usefulness of mobile learning content (PU)	Subnorm → PU	Supported
H8	Social subjective norm (Subnorm) will positively affect perceived facilitation condition (PF)	Subnorm → PF	Supported
H9	Social subjective norm (Subnorm) will positively affect perceived ease of use of mobile learning content (PE)	Subnorm → PE	Rejected
H10	Social image (Image) will positively affect participants' behavioral intention of adopting mobile learning (BI)	Image → BI	Supported
H11	Social Image (Image) will positively affect the perceived usefulness of mobile learning content (PU)	Image → PU	Supported
H12	Social image (Image) will positively affect perceived ease of use of mobile learning content (PE)	Image → PE	Supported
H13	Voluntariness (Volun) will positively affect perceived facilitation condition (PF)	Volun → PF	Supported
H14	Personal innovativeness (Innov) will positively affect participants' behavioral intention of adopting mobile learning (BI)	Innov → BI	Rejected
H15	Personal Innovativeness (Innov) will positively affect perceived usefulness of mobile learning content (PU)	Innov → PU	Rejected
H16	Personal Innovativeness (Innov) will positively affect perceived ease of use of mobile learning content (PE)	Innov → PE	Supported
H17	Social image (Image) will positively affect personal innovativeness to try out mobile learning (Innov)	Image → Innov	Supported
H18	Social subjective norm (Subnorm) will positively affect personal innovativeness to try out mobile learning (Innov)	Subnorm → Innov	Supported
H19	Voluntariness (Volun) will positively affect personal innovativeness to try out mobile learning (Innov)	Volun → Innov	Supported

Pedagogical factors

From the path analysis, hypotheses 1 (PU → BI), 2 (PE → BI), and 3 (PF → BI) are supported with significant β *values* of .46 ($p < .001$), .24 ($p < .001$), and .38 ($p < .05$),

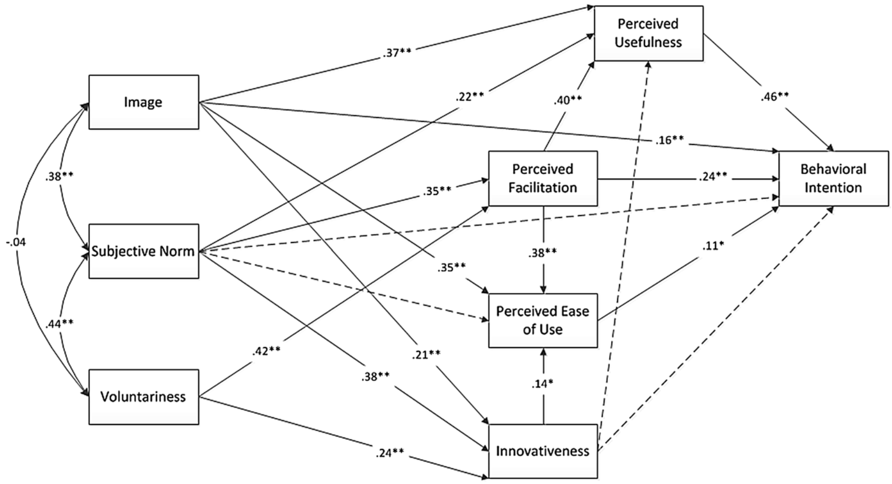

Fig. 2 Path analysis of relationships of mLearning adoption intention and pedagogical, social, and personal factors. * Significant at p < .05. ** Significant at p < .001

Table 6 Summary of overall goodness-of-fit indices

	χ^2	*df*	p	CFI/TLI	RMSEA	SRMR
mLearning intention model	11.378	6	.077	.994/.975	.056	.017
mLearning intention model with insignificant paths deleted	16.113	10	.096	.993/.983	.047	.022

Table 7 *R*-square estimates with insignificant paths deleted

Observed variance	R^2	SE
BI	0.592	0.037
PU	0.529	0.040
PE	0.388	0.045
PF	0.427	0.045
Innov	0.376	0.046

respectively. These results indicate that pedagogical merits are considered the most critical and direct influences of students' behavioral intentions toward mobile learning, with students' perceived usefulness of mobile learning content having the greatest influence. Perceived facilitation and ease of use are also strongly associated with intention. As facilitation increases, it may become easier for learners to engage in mobile learning. Also, students may value facilitated mobile learning activities more highly because of the instructor's influence.

The three pedagogical factors strongly interrelate with each other. From the path model, H4 (PF → PU) and H5 (PF → PE) are supported with significant β value of .40 and .38

respectively ($p < .0001$). Essentially, in facilitated environments it seems likely that interaction with instructors and peers may add to perceptions of usefulness and ease of use. For this reason, facilitation should be given critical consideration when delivering mobile learning activities.

Our model shows that Chinese university students are most likely to engage in mobile learning when they find it pedagogically useful, an action that demonstrates a high degree of practicality, and when it is easy to use. These findings confirm earlier research on the TAM model and its successors (e.g., Davis 1989; Venkatesh and Davis 2000; Venkatesh and Bala 2008), and mobile Internet adoption (Lu et al. 2005), and extend their findings to the mobile learning context. These two driving forces for mobile learning adoption—usefulness and ease of use—are quite logical as mobile learning will not serve its purpose if it does not support an instructional objective or if its use adds unnecessary complexity to the learning context.

Social factors

Out of the eight hypotheses related to social factors, six are supported. H10 is supported because the direct path (Image → BI) was significant with β value of .16 at $p < .0001$, while H6 is not supported, with an insignificant path (Subnorm → BI). These results suggest that Chinese students consider how their identity reflects their behaviors. In other words, they are more likely to try out mobile learning if such behavior makes them look "good" among their peers. However, these students are not concerned with what others are doing or encouraging them to do in a mobile learning context. Combined, these two findings suggest that Chinese students trust their own judgments about how mobile learning will affect their social status, and make decisions about mobile adoption learning accordingly.

Additionally, social factors are positively correlated with pedagogical factors. H11 (Image → PU), and H12 (Image → PE) are supported with β value of .37 and .35, respectively ($p < .001$). These two significant paths indicate that social image positively impacts Chinese students' perceptions related to usefulness and ease of use. Since PU and PE directly impact students' intent to adopt mobile learning, social image indirectly affects BI through the mediation of PU and PE in addition to its direct influence on BI.

The social subjective norm also positively influence PU and PF with significant β values of .22 and .35 respectively ($p < .001$), which means H7 (Subnorm → PU) and H8 (Subnorm → PF) were supported. Similarly, mediated through PU and PF, social subjective norm indirectly impacts BI. On the other hand, H9 (Subnorm → PE) was rejected due to the insignificant path coefficient value. While the opinions and encouragement of others does not help individual students determine whether mobile learning will be easy for them to use, important social factors can influence how useful a learner perceives mobile learning. Also, those people who encourage a learner to adopt mobile learning may also serve as a source of support for mobile learning, particularly when they are teachers or peers.

Finally, the path from voluntariness to PF is significant at $p < .001$ with β value of .42, which supports Hypothesis 13. This indicates that when Chinese students try out mobile learning out of their free will, they do not expect their experience to be a solitary one. Instead, they anticipate that others will be present to help them learn and learn alongside them. Through the mediation of PF, voluntariness also indirectly influences BI.

In summary, in terms of social factors, image had the greatest influence on students' behavioral intention to adopt mobile learning. In other words, social status is a concern of these students. They are aware that their use of mobile learning communicates something about them to others. This finding is not surprising, since mobile phones have been a marker of status in Chinese culture since their introduction (Lu et al. 2008; Samson and Hornby 1998; Wei 2006). Interestingly, the subjective norm was not found to directly affect behavioral intention to adopt mobile learning, suggesting that the users construct their own sense of image and do not rely on their direct social contacts to influence the image they should convey. Nonetheless, there is an indirect relationship here, and so the actions of one's peer group should not be entirely discredited in this context.

Personal innovativeness

Six hypotheses were related to personal innovativeness, four of which were supported. Hypothesis 14 (Innov → BI) was rejected, indicating that personal innovativeness is not a significant indicator of Chinese students' behavioral intention for mobile learning. This result may be explained by the broad definition of mobile learning that we communicated to students in the survey: "Mobile Learning refers to any formal or informal learning inquiry or behaviors conducted through mobile devices, e.g., view course material from a mobile learning system, conduct a scenario-based learning through a mobile application, participate an academic discussion groups, make a mobile web inquiry, etc." With this definition in mind, students may have been able to identify various mobile learning activities in which they are already engaged. If these students do not perceive themselves as innovators or early adopters (Rogers 1995) they would not strongly associate personal innovativeness with mobile learning.

Hypothesis 16 (Innov → PE) was supported at $p < .05$ with β value of .14, while H15 (Innov → PU) was rejected. Learners with higher senses of innovativeness are more confident that using the technology will be easy. However, just because something is new and perceived as easy or achievable does not mean it will be useful. To that end, the Chinese students take a critical view of new technologies and do not assume that just because the technology is new or innovative that it will serve a purpose in their education. Other factors, like perceived learning needs and social influence are more influential than innovativeness.

All three social factors are positive indicators of personal innovativeness, and H17 (Image → Innov), H18 (Subnorm → Innov), and H19 (Volun → Innov) are supported. The significant path from Subnorm → Innov ($\beta = .38$, $p < .0001$) indicates that the influential people can positively impact students' innovativeness in mobile learning. The path from Image → Innov was significant with a β value of .21 ($p < .0001$). Students are willing to try a new learning experience if doing so reflects their expected social status. Finally, Volun → Innov was a significant path with a β value of .24 ($p < .0001$), which indicates that students who to adopt mobile learning voluntarily are more likely to be innovative and creative in that venture.

Thus, in this category we find that our participants clearly did not perceive mobile learning as an innovative act, although they do consider innovativeness as a factor that is reflected in one's image. Combined with the significant influences found on students' behavioral intentions on mobile learning from pedagogical factors, this finding suggests that learners view mobile learning as a potential mainstream learning option at this time. The broad definition used in the survey likely fostered this perception: although the respondents may not have previously engaged in robust, transformative mobile learning experiences (see O'Sullivan 1999 and Ng'ambi 2013 for discussions of transformative learning and transformative pedagogy in the context of educational technologies, respectively), the concept of looking up information or communicating with someone else about coursework via a mobile device is sufficiently common to feel within reach.

Limitations

This study has two main limitations. First, our broad definition of mobile learning may have caused use to overlook certain issues, such as the influence of students' socioeconomic status and access and equity issues. Our definition was inclusive of simple activities, such as looking up words in a dictionary or texting a friend for help, and complex ones such as collaborating with classmates on a creative project using an app. This definition is functional for many purposes, but may not accurately reflect the conditions needed to support classroom integration of mobile learning activities (Dennen and Hao 2014b). There are a wide range of learning activities that may constitute mobile learning, both formal and informal, with instructivist, situated, and constructionist underpinnings (Pimmer et al. 2016). Some of these activities may require late-model smartphones, whereas others may be manageable on an older phone. Had mobile learning been defined in one of these ways, the findings may have differed, and it is difficult to know exactly what the respondents envisioned as specific examples of mobile learning when responding the survey. Students from lower socioeconomic status backgrounds who own older models of phones with lesser hopes for obtaining a new model may have different perceptions of their ability to participate in certain types of mobile learning activities than their more affluent peers.

Second, sampling bias may exist in this study. Our participants were from one university, and participation was voluntary. Even though the participants were representative to the university's general demography, it is possible that the people who chose to participate were those who were more interested in the topic of mobile learning. We believe our results can be generalized to a certain degree in the Chinese culture, because the chosen university is similar to others in the Chinese university system in terms of student age range, cell phone ownership, and campus technology environment. However, we cannot ascertain that our results can be generalized to other countries with different cultural backgrounds.

Conclusion and future direction

In closing, mobile learning adoption is influenced by a confluence of factors, but led by practical ones—perceived educational need and ability to use. Factors like image, peer influence, and innovativeness demonstrate the complexity with which learners perceive mobile learning; they believe that it is not only a means to an end but also that it communicates information about their status in society. These factors are, in some ways, more important in a practical sense than they may seem in the model. Given the BYOD model of mobile learning promoted in many educational settings (Dennen and Hao 2014b; Johnson et al. 2013), device adoption behavior is a prerequisite for the learning behavior.

Future studies might confirm if the positive influencers remain the same and at the same levels across cultures and in different countries, since factors such as cost, market penetration of devices, and educational beliefs and values may alter the role that pedagogical, social, and personal factors play. Additionally, differences in perception might be measured in different educational contexts (e.g., K-12, continuing education), and with specific mobile learning activities in mind. It seems likely that this topic will remain a dynamic one in the near future. The future landscape of beliefs about mobile learning use in higher education will not only be shaped by technological and pedagogical advances, but also by the upcoming generation of higher education students who are increasingly likely to have experienced mobile learning as part of their elementary and secondary level education.

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