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Investigating the structural relationship among perceived innovation attributes, intention to use and actual use of mobile learning in an online university in South Korea

Young Ju Joo, Kyu Yon Lim, Eugene Lim
Ewha Womans University, Republic of Korea

The purpose of this study was to investigate the effect of perceived attributes of innovation, that is, relative advantage, compatibility, complexity, trialability and observability on learners' use of mobile learning. Specifically, this study employed structural equation modeling in order to examine the causal relationships among perceived attributes of innovation, learners' intention to use mobile learning and the actual use of mobile learning. Analysis of 200 college student respondents who registered for a course offered by an online university in South Korea revealed that relative advantage and complexity had significant effects on the intention to use mobile learning, whereas trialability and observability did not. Further, the intention to use mobile learning had a direct positive effect on learners' actual use of mobile learning.

Introduction

Information and communication technologies, including digital and mobile technologies, have been considered potentially powerful enabling tools for educational improvement. This is especially true in South Korea, where 82.5% of the population are Internet users and 78.5% smartphone users as of 2012 (KISA, 2012), and mobile learning using smartphones and tablet PCs is drawing keen attention from educational researchers as well as practitioners. By definition, mobile learning is any type of learning that takes place with the help of a mobile device (Quinn, 2000). Taking a learner's perspective, O'Malley et al. (2003) stated that mobile learning is learning that happens when learners are not at a fixed, predetermined location. Suggested advantages include that it enables learners to learn in a self-directed and self-paced mode with enhanced accessibility to content and resources (Barker, Krull, & Mallinson, 2005; Kukulska-Hulme & Traxler, 2005).

Given that higher education institutions have been seeking technologies for effective and efficient delivery of education to fit learners' needs (Dooley & Murphrey, 2000), the push to utilise mobile devices is not surprising. In 2011, the South Korean Ministry of Education, Science and Technology (KMEST) announced a government-level financial support plan to promote mobile learning through online universities, where all teaching and learning activities as well as university administration occur in online space. Seven online universities were subsequently funded through this plan (KMEST, 2011). By early 2012, 74% of the courses offered by online universities in South Korea had provided mobile learning services along with the traditional Internet-based service (Korea National IT Industry Promotion Agency [KNIPA], 2012). The integration of these mobile learning services was designed to substantially improve access to courses and course resources. That is, learners could, potentially, study anytime and anywhere, and the affordances of the mobile technology would better facilitate real-time or immediate interactions among online learners and instructors (Corbeil & Valdes-Corbeil, 2007).

However, adoption of mobile learning services by learners has been slow (Keller, 2011). For example, part-time online learners of the Open University in the United Kingdom tend not to be supportive of mobile learning using smartphones and PDAs due to cost, battery life, technical difficulties, and inadequate screen sizes and interface (Platts, 2009). Furthermore, they did not prefer studying on the move using mobile devices. In a similar vein, it seems that mobile learning for online learners, in South Korea, is not yet seen as a priority or necessity. According to a survey from the Korea National IT Industry Promotion Agency (KNIPA, 2012), only 3.1% of online learners were using a mobile service for learning in 2011. Another survey on the usage of mobile services conducted by the Korea Information Society Development Institute (KISDI, 2011) reported that only 5.1% of the adult mobile users considered the purpose of using mobile devices as learning, while other major purposes included utilizing various mobile applications (33.1%), searching for information on the Internet (24.6%) and experiencing new media (15.6%). The reasons for such low levels of uptake are unclear, but don't appear to be linked

to ownership of devices in South Korea, given that 78.5% of the population are smartphone users as mentioned above (KISA, 2012). Clearly we need to improve our understanding of the factors that actively promote or discourage the use of mobile learning services if we are to maximise the effectiveness and benefit of mobile learning initiatives such as those undertaken by South Korea's online universities.

Conceptually, it helps to view mobile learning as an innovation that is available to learners, instructors and administrators of online universities. According to Rogers (2003), innovations are ideas, products, practices and technologies perceived as being new by an individual. Thus, mobile learning in online universities in South Korea represents an innovation that enables learners to take courses by accessing learning materials and communicating with others via mobile applications. Diffusion is related to innovation and is the process by which innovation is communicated through certain channels over time among the members of a social system. Diffusion of innovation theory, then, considers how, why and at what rate new ideas and technologies spread out through cultures (Rogers, 2003). Based on a series of investigations, Rogers found that people have different attitudes towards the innovation in terms of adopting or rejecting new ideas. He identified five types of adopters – innovators, early adopters, early majority, late majority and laggards. Also, certain innovations spread more quickly than others. Adopter types and the rate of adoption are together explained by the characteristics of an innovation, as perceived by the members of a social system.

Specifically, there are five characteristics that determine the rate of adoption, which are (1) relative advantage, (2) compatibility, (3) complexity, (4) trialability and (5) observability (Rogers, 2003). Relative advantage is the degree to which an innovation is perceived as being better than its precursor, which is consistent with the concept of perceived usefulness from the technology acceptance model (TAM) by Davis, Bagozzi, and Warshaw (1989). There is a high chance of adoption of an innovation, such as mobile learning in this study, when users perceive the innovation to be useful for them. Compatibility is the degree to which an innovation is perceived as being consistent with the existing values, needs and past experiences of potential adopters. If online university students perceive mobile learning to be consistent with their values and needs, they will be more likely to use the mobile learning service to support their study. Complexity is the degree to which an innovation is perceived as being difficult to use. This is opposite to the concept of perceived ease of use from TAM (Moore & Benbasat, 1991). Although it has been argued that complexity is not as critical as relative advantage or compatibility (Helsel, 1972), its importance has been well recognized more recently in the field of user interface and usability, where it has the potential to be a substantial barrier to adoption (Nielsen, 1993). Trialability is the degree to which an innovation may be experimented with before adoption. Trialability is important because users may experience trial and error beforehand, which can reduce the level of user anxiety once the innovation is adopted. Lastly, observability is the degree to which the results of an innovation are observable to others. This suggests that if there are no opportunities for observation or exposure, diffusion will take more time.

All in all, according to Rogers (2003), most individuals evaluate an innovation, not on the basis of scientific research by experts, but through subjective evaluations of the characteristics of the innovation. For this study, therefore, learners' perception of mobile learning as an innovation played a critical role in determining their usage behavior. That is, learners who perceive mobile learning as being relatively advantageous to them, compatible with and less complex than their existing practices, and with trialable and observable benefits, are more likely to adopt mobile learning.

Relationships between perceived attributes of innovation and intention to adopt

Diffusion of innovation has been employed to evaluate the spread of a number of new educational ideas and practices (e.g., Chang & Tung, 2008; Kuo & Yen, 2009; Lai & Chen, 2011). Studies on the relationships between perceived attributes of innovation, the intention to use and the actual usage are particularly relevant to this study. With respect to mobile use, Sheng, Wang, and Yu (2011) found that among the five perceived attributes of innovation, only trialability failed to predict the intention to use mobile banking in China. In the field of education, Helsel (1972) investigated the correlations between teachers' acceptance of innovation and innovation characteristics with 25 teachers. He reported that relative advantage and compatibility had significant correlations with teachers' intention to use. More recently, Fu, Yue, Li, Zhang, Zhang, and Gao (2007) studied the diffusion of e-learning adoption in China, investigating learners' perceptions and attitudes toward adopting e-learning. They explored the factors

affecting the e-learning adoption intention from an innovation adoption perspective based on Rogers' (2003) model. According to their results, relative advantage, compatibility, trialability and observability all impacted on users' intention to adopt e-learning. Complexity was not a significant factor, but the authors attributed this to cultural differences between China and the Western world. In a recent Taiwanese study, based on a hybrid of Rogers' (2003) model and Davis et al.'s (1989) TAM research model, Lee, Hsieh, and Hsu (2011) reported that all of the five attributes significantly affected users' intention to adopt an e-learning system in their workplace. Lastly, Jebeile and Abeysekera (2010) investigated 485 college students' intention to adopt an online computer-assisted learning module. The researchers excluded trialability from the research question, as all of the research participants appeared to have had an opportunity to try the innovation beforehand due to the fact that the innovation was a required component for learning. Their findings indicate relative advantage, compatibility, complexity and observability all significantly predicted learners' intention to adopt the intervention.

In summary, there is a substantial body of research on the perceived attributes of innovation on which we can draw. However, individual approaches do vary, with the exclusion of individual attributes and/or the combination of the Rogers' (2003) and Davis et al.'s (1989) TAM models being relatively common. While relative advantage was a significant factor in the intention to adopt in most studies, the importance of other attributes, notably complexity and observability, tended to vary according to the context of use.

Relationships between intention to use and actual use

Intention of adoption is a psychological state of the user arising right before the actual adoption of an innovation (Davis et al., 1989). Theories on technology acceptance illustrate the relationship between intention of adoption and actual adoption – that is, usage of the device. Specifically, the theory of reasoned action (TRA) by Ajzen and Fishbein (1980), theory of planned behavior (TPB) by Ajzen (1991), and TAM by Davis et al. (1989) all state that the intention of adoption predicts actual use. However, because it is practically difficult to measure actual adoption, many empirical studies have used intention as a proxy for actual usage to investigate diffusion of an innovation (Shin, 2011). Relatively few studies have examined the relationship between intention to use and actual use. Among these, Venkatesh and Davis (2000), Heijden (2003), Dishaw and Strong (1999) all reported that intention had a significant influence on the actual use of an online portal, web site, and information technology respectively. In relation to mobile use, both Kim (2012) and Cheong and Park (2005) reported positive relationships between users' intention to use and their actual use of mobile services. However, none of these studies focused on a general mobile or educational usage context.

The preceding review of previous studies of diffusion of innovation suggests that, in general, the various perceived attributes of innovation do appear to influence the intention to use. However, many of these studies employ correlations and regression analysis, which do not explain the causal relationships in a comprehensive research model, and few if any of them deal with the intention to use and the actual use of mobile learning as an innovation. This study attempts to address both these shortcomings by investigating mobile learning as an innovation of interest in an online university, and exploring the causal relationships among the variables based on Rogers' diffusion of innovation theory (2003). The purpose of this study is to investigate the effect of perceived attributes of innovation, that is, relative advantage, compatibility, complexity, trialability and observability on learners' use of mobile learning in an online university where all of the teaching, learning and administrative activities occur online. In simple terms, this study seeks to identify the barriers to the adoption of mobile learning services in an online university context from the perspective of the attributes of innovation.

Methodologically, this study employs structural equation modeling (SEM) in order to examine the structural relationships among perceived attributes of innovation, learners' intention to use mobile learning, and the actual use of mobile learning. A hypothetical model for this study is illustrated in Figure 1. This model can be represented by the following two research hypotheses:

- Hypothesis 1: Relative advantage, compatibility, complexity, trialability and observability have direct effects on learners' intention to use mobile learning.
- Hypothesis 2: Learners' intention to use mobile learning has a direct effect on learners' actual use of mobile learning.
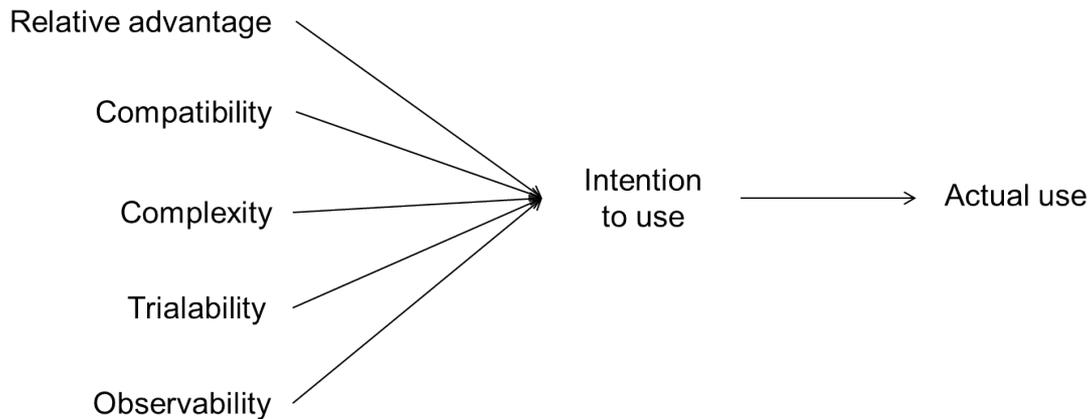
Figure 1. Hypothetical research model

Methods

Participants and contexts

The research participants were 480 students enrolled in an elective, three-credit course in the 2012 autumn semester at an online university in South Korea. A total of 200 completed responses were analyzed (overall response rate, 41.6%), consisting of 80 males (40%) and 120 females (60%).

The course content was delivered via both web and mobile platforms, although the mid-term and final exams were only accessible via the web platform. The mobile platform was available for iOS and Android smartphones and tablets, and supported all of the key features of the web platform, namely course announcement, Q&A, video lectures, discussion boards, social networking services, academic status information, and so on. Students were free to use either or both platforms to support their learning. The course dealt with how to improve general problem-solving skills and reflection skills in everyday lives.

Measurement instruments

The construct definitions and the measurement instruments developed by Moore and Benbasat (1991) were adopted to measure the perceived attributes of innovation, that is, the relative advantage, compatibility, complexity, trialability and observability of the mobile learning platform. Learners' intention to use mobile learning was measured using the instruments developed by Taylor and Todd (1995). Both were translated into Korean by the researchers, and some of the items were modified in order to fit the mobile learning context. For example, the original item "I think that using a PWS (personal workstation) fits well with the way I like to work" for the compatibility factor was modified as "I think that using a mobile device fits well with the way I like to study". The modified instruments were reviewed by two experts in the field of educational technology. The measurement instruments used for this study are summarized in Table 1.

Regarding the perceived attributes of innovation, *relative advantage* refers to the degree to which an innovation is perceived as being better than its precursor. Eight questions were used for this study; the sample item is "Using a mobile device makes it easier to take this course". Cronbach's alpha from Moore and Benbasat (1991) was .90, and the study data provided a Cronbach's alpha of .92. *Compatibility* is the degree to which an innovation is perceived as being consistent with the existing values, needs and past experiences of potential adopters. There were four items suggested by Moore and Benbasat (1991); the sample item is "Using a mobile device fits into my learning style". Cronbach's alpha from the prior research was .86, and the one from the current data was .91. *Complexity* refers to the degree to which an innovation is perceived as being difficult to use. Six items suggested by Moore and Benbasat (1991) were

used for this study, and one of them is "Using a mobile device requires great mental effort". Cronbach's alpha from the prior research was .84, and the alpha from the study data was .90. *Trialability* indicates the degree to which an innovation may be experimented with before adoption. There were five items to measure trialability; the sample item is "Before deciding whether to use any mobile applications for this course, I was able to properly try them out". Cronbach's alpha from the prior research was .71, while the study data provided an alpha of .90. Lastly, *observability* refers to the degree to which the results of an innovation are observable to others. Four items suggested by Moore and Benbasat (1991) were used for this study; the sample item is "I have seen what others do to take online courses using their mobile device". Cronbach's alpha from the prior research was .83, and the alpha from the current data was .85. All of the instruments employed a 5-point Likert scale.

Table 1
List of measurement instruments

	Variables	No. of items	Source	Scales	Cronbach's alpha
Perceived attributes of innovation	Relative advantage	8	Moore & Benbasat (1991)	5-point Likert scale	.92
	Compatibility	4			.91
	Complexity	6			.90
	Trialability	5			.90
	Observability	4			.85
Intention to use		3	Taylor & Todd (1995)		.93
Actual use			NA		

Note. Log data were collected from the learning management system for the actual use of mobile learning application.

Learners' *intention to use* mobile learning indicated the intention of learners to use the mobile application provided by the university so they can acquire the necessary information on the course or watch video lectures using their mobile device. The instrument developed by Taylor and Todd (1995) was used, and the sample item is "I intend to use the mobile learning service frequently this term". There were three items included in the instruments using a 5-point Likert scale. Cronbach's alpha from the prior research was .91, and the alpha from the current data was .93.

Lastly, *actual use* of the mobile learning was measured based on the frequency of access to the course via mobile application throughout the semester. The frequency was counted right after the course was completed, and the access to the mobile application required a login process to the mobile-based learning management system, providing log data for each individual. The range of the access frequency appeared from a minimum of 0 to a maximum of 435, meaning that there were students who did not use the mobile service at all, because the use of mobile learning application was not a requirement for completing the course.

Data collection procedure and analysis

Two weeks after the mid-term exam, an online survey questionnaire on the perceived level of relative advantage, compatibility, complexity, trialability and observability, and the intention to use the mobile learning was administered to the students. The frequency of access to the mobile application was counted after the completion of the course.

SPSS was used to conduct a descriptive analysis and test the validity and reliability of the measurement scores. For the structural equation modeling, AMOS was used to conduct a confirmatory factor analysis and assess the fit of the measurement and structural model. Item parcels were used for the unidimensional factors, and the goodness of fit indices adopted for this study were as follows: minimum sample discrepancy (CMIN), Tucker-Lewis index (TLI), comparative fit index (CFI) and root-mean-square error of approximation (RMSEA). The effects among the variables were tested at the significance level of .05.

Results

Descriptive statistics and correlations among the variables

The correlational analysis revealed some correlation coefficients of above .80, This suggested the possibility of multicollinearity due to the high correlation among predictors. An exploratory factor analysis was therefore conducted (Kutner, Nachtsheim, Neter, & Li, 2004), using principal axis factoring and direct oblimin rotation to assist with the interpretation of results. The results from this analysis suggested five factors: relative advantage, complexity, trialability, observability and intention to use. One item from complexity and all four items from compatibility showed double loading, and were removed from the research model. That is, compatibility was not identified as a single factor. According to Moore and Benbasat (1991), compatibility was conceptually separated from the relative advantage, and each demonstrated high reliability. However, they reported that the result from the principal component analysis indicated that compatibility and relative advantage were revealed as a singular factor, requiring further elaboration of the instrument. Kim and Kim (2002) also reported that the compatibility was not extracted as a single factor. This study confirms this, leaving us with four perceived attributes of innovation: relative advantage, complexity, trialability and observability.

For the unidimensional factors of relative advantage, complexity, trialability, observability and intention to use, item parcels were used to minimize any possible overweight on a particular variable in the suggested model (Kishton & Widaman, 1994), to reduce the number of parameters to estimate, and to ensure the assumption of multivariate normality (Bandalos, 2002). In terms of structural equation modeling, a parcel can be defined as an aggregate-level indicator comprised of the sum or average of two or more items (Kishton & Widamn, 1994), and labeled as 1, 2, and so on. For example, eight items for relative advantage have been randomly assigned into relative advantage 1 with four items, and relative advantage 2 with another four items. The means, standard deviations and correlational coefficients for all the variables are presented in Table 2.

Table 2
Means, standard deviations and correlation coefficients

(*n* = 200)

Measurement variables	Correlations of measurement variables										
	1	2	3	4	5	6	7	8	9	10	11
1. Relative advantage 1	-										
2. Relative advantage 2	.87*	-									
3. Complexity 1	-.63*	-.63*	-								
4. Complexity 2	-.67*	-.68*	.87*	-							
5. Trialability 1	.57*	.52*	-.56*	-.58*	-						
6. Trialability 2	.56*	.49*	-.57*	-.59*	.77*	-					
7. Observability 1	.51*	.44*	-.45*	-.45*	.52*	.59*	-				
8. Observability 2	.61*	.52*	-.52*	-.52*	.58*	.61*	.78*	-			
9. Intention to use 1	.64*	.63*	-.66*	-.66*	.51*	.60*	.39*	.51*	-		
10. Intention to use 2	.66*	.63*	-.68*	-.67*	.46*	.55*	.40*	.53*	.86*	-	
11. Actual use	.25*	.29*	-.38*	-.39*	.17*	.23*	.20*	.27*	.41*	.38*	-
Mean	3.46	3.57	2.54	2.55	2.91	2.82	3.06	3.09	3.37	3.51	35.39
Standard deviations	.79	.78	.83	.84	.79	.96	.90	.82	1.14	.98	73.55
Min.	1	1	1	1	1	1	1	1	1	1	0
Max.	5	5	5	5	5	5	5	5	5	5	435

$^*p < .05$

Assessment of measurement model

Before moving on to the structural model, the goodness of fit indices for the a priori measurement model was analyzed using maximum likelihood estimation (Kline, 2005). As presented in Table 3, the results indicate that the measurement model showed a good fit with the data collected, when compared to the suggested criteria (e.g., TLI = .985, RMSEA = .054). In other words, the measurement of latent variables included in the model were valid, and more specifically, discriminant validity among variables as well as convergent validity for each latent variable and corresponding item parcels were confirmed (Moon, 2009).

Table 3
Fit statistics for the measurement model

	CMIN(χ^2)	*p*	*df*	TLI	CFI	RMSEA (90% confidence interval)
Measurement model	39.39	.03	25	.985	.992	.054 (.015 ~ .085)
Criteria (Browne & Cudeck, 1993)	-	-	-	> .90	> .90	< .08

(n = 200)

Note. RMSEA less than .05 indicates close fit, less than .08 reasonable fit (Browne & Cudeck, 1993)
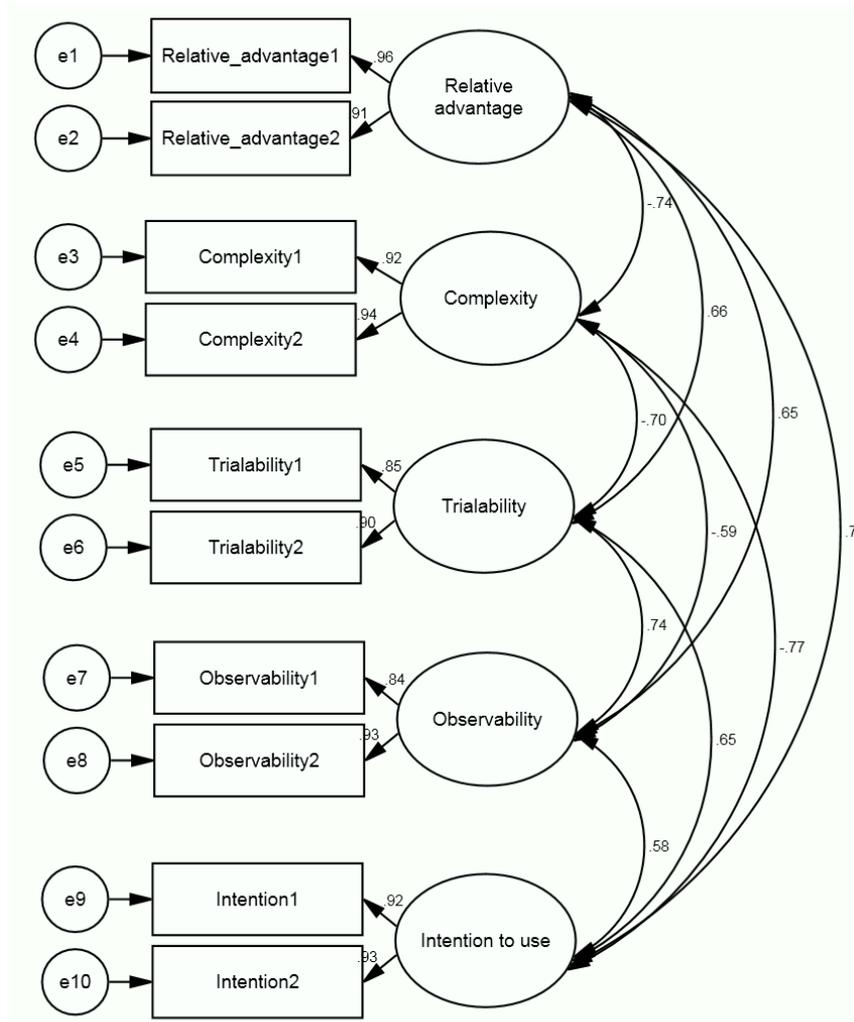
Figure 2. Results of confirmatory factor analysis

The results from the confirmatory factor analysis on the measurement model provided detailed information on the convergent validity and discriminant validity. All of the factor loadings were higher than .50, ranging from .84 to .96, indicating good convergent validity (Hair, Anderson, Tatham, & Black, 1992). Discriminant validity was also good, given that all the correlations among latent variables were lower than the absolute value of .80, ranging from .58 to .77, as illustrated in Figure 2.

Structural model and hypothesis testing

Since the goodness of fit indices for the measurement model met the criteria, the fit of the structural model was analyzed using maximum likelihood estimation. According to Table 4, the structural model exhibited a good fit with the collected data, when compared to the suggested criteria (e.g., TLI = .982, RMSEA = .054). That is, the suggested research model represents the causal relationships among the variables, and the path coefficients of the structural model are statistically significant, as shown in Table 5.

Table 4
Fit statistics for the structural model

$(n = 200)$

	CMIN(χ^2)	*p*	*df*	TLI	CFI	RMSEA (90% confidence interval)
Structural model	54.08	.02	34	.982	.989	.054 (.024 ~ .081)
Criteria (Browne & Cudeck, 1993)	-	-	-	> .90	> .90	< .08

Table 5
Path coefficients of the structural model

$(n = 200)$

	Variables	Unstandardized B	Standardized β	*SE*	*t*	*p*
Intention to use	← Relative advantage	.449	.302	.127	3.539[*]	.000
	← Complexity	-.605	-.453	.121	-5.015[*]	.000
	← Trialability	.146	.120	.121	1.208	.227
	← Observability	.035	.025	.120	.291	.771
Actual use	← Intention to use	30.104	.431	4.742	6.348[*]	.000

[*]$p < .05$

Relative advantage and complexity had significant effects on the intention to use (Relative advantage: β = .302, *t* = 3.539, *p* < .05; Complexity: β = -.453, *t* = -5.015, *p* < .05), whereas trialability and observability did not. Thus, based on the fit of the structural model, non-significant path coefficients, that is, paths from trialability and observability to the intention to use, were removed from the model in order to make it more concise. The CMIN statistic was used to examine the statistical difference between the original and modified model. There was no significant difference in terms of the goodness of fit ($\Delta\chi^2$ = 2.79, p = .247), and the modified model exhibited a good fit (CMIN = 56.87; TLI = .982; CFI = .988; RMSEA = .052). As a result, the modified structural model was confirmed as the final, more concise research model. The standardized path coefficients of the modified model were reexamined, as illustrated in Figure 3.
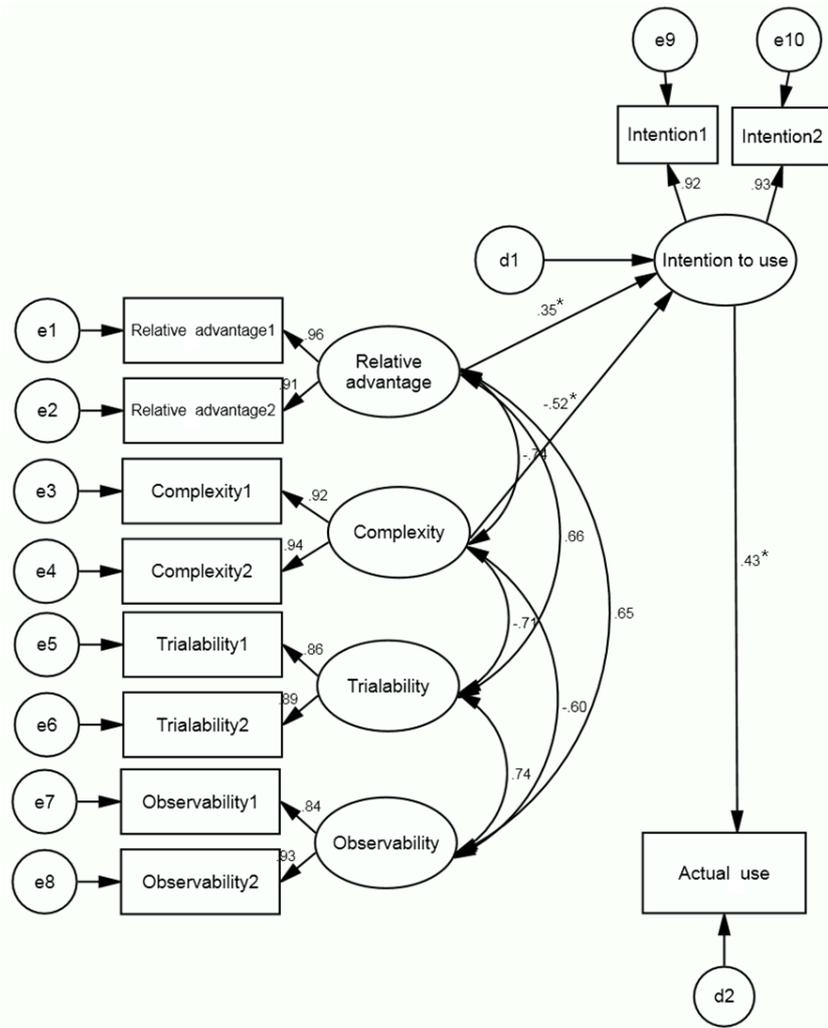
Figure 3. Modified model with standardized path coefficients

The relationships among the variables in the modified model were as follows: Firstly, relative advantage and complexity had significant effects on the intention to use (relative advantage: β = .348, *t* = 4.388, *p* < .05; complexity: β = -.522, t = -6.413, p < .05). More specifically, complexity showed a significant negative effect on intention to use, meaning that the higher the complexity of mobile learning application, the lower the intention to use of the learners. Secondly, the intention to use had a significant effect on the actual use of mobile learning (β = .431, *t* = 4.763, *p* < .05). Thus, the first research hypothesis, that relative advantage, compatibility, complexity, trialability and observability have direct effects on learners' intention to use mobile learning was only partially supported, because compatibility, trialability and observability did not have significant effects on the intention to use. The second research hypothesis, that learners' intention to use mobile learning has a direct effect on learners' actual use of mobile learning, was supported.

Discussion

The purpose of this study was to examine the effect of perceived attributes of innovation, that is, relative advantage, compatibility, complexity, trialability and observability on learners' intention as well as the actual use of mobile learning, based on the diffusion of innovation theory (Rogers, 2003). The results suggest that the perceived level of relative advantage of an innovation affects the intention to use, while trialability and observability do not. The effects of relative advantage on the intention to use echoed the results from previous studies (Eriksson, Kerem, & Nilsson, 2008; Karavasilis, Zafiropoulos, & Vrana, 2010; Lancaster & Taylor, 1988; Sheng et al., 2011). Given that the 88% of the learners registered for Korean online universities combine work and study (KNIPA, 2012), some advantages of mobile learning,

such as accessibility, immediacy and portability (Barker et al., 2005), might have appealed to the Korean learners by providing just-in-time learning opportunities whenever necessary during work, which is likely to facilitate intention to use. This suggests that online universities planning to initiate or expand the mobile learning intervention should focus on relative advantage when promoting their new solution.

Complexity had a negative effect on the intention to use, supporting the results from some of the prior research in marketing fields (Eriksson et al., 2008; Sheng et al., 2011). This result suggests that the user interface of mobile learning applications should be designed in an intuitive, user-friendly manner in order to minimize the perceived level of complexity (Nielsen, 1993). Open University students, for example, reported that inadequate or unsatisfactory user interfaces were a distinct barrier to the use of mobile devices for learning (Platts, 2009). While many barriers to adoption are financial or technical (e.g., purchase and network costs, battery life, software compatibility and screen sizes) and outside the educator's influence, researchers and practitioners typically have considerable control over both interface and educational design decisions. Clear guidelines for designing mobile learning applications are useful here, since some accepted design principles for e-learning don't necessarily translate to mobile devices which have different technology affordances, such as smaller screens and touch-based interfaces, to standard laptops or desktop computers. For example, extraneous cognitive load tends to be generated when lengthy texts and large chunks of materials are displayed through mobile devices. Also, Wang, Wu, and Wang (2009) mentioned reduced input capabilities as challenges for using mobile devices for learning. Further investigation of mobile-specific design principles is required in order to increase both in-depth understanding and actual use of mobile learning in online university context.

Regarding trialability, which did not show significant effects on the intention to use, this result supports the claims made by previous studies (Lancaster & Taylor, 1988; Sheng et al., 2011). In fact, the mean score of the trialability was as very low as 2.87. As the survey asked such items as "Before deciding whether to use the mobile learning applications, I was able to properly try them out" and "I was permitted to use the mobile learning application on a trial basis long enough to see what it could do", the university should provide additional support for users, such as a orientation session for a substantial period of time beforehand or an online trial demo session which would allow learners to become familiar with the mobile learning application more conveniently. According to KNIPA (2012), 37.2% of the online university students in South Korea are in their 40s or above, suggesting one third of the learners may need a sufficient amount of trial and error experience in order to use mobile application for learning. Observability also showed an insignificant effect on the intention to use, which is not consistent with prior research (Jebeile & Abeysekera, 2010; Lee et al., 2011; Suh, 2011). Observability may not have a critical role in the online university context, where students are located at a distance, unlike other traditional face-to-face university learning. More specifically, in online universities where learners hardly meet each other face-to-face, the observability factor is less important as other factors in the diffusion model.

On the other hand, the intention to use significantly affected the actual use of mobile learning, which supports the studies by Kim and Kim (2002) and Venkatesh and Davis (2000). Because the actual use in this study was counted as the frequency of access to the mobile learning application, the study result suggests that the higher the learners' intention to use the application, the more often they use it. That is, as intention resulted in action in the mobile learning context, and as intention was affected by the level of relative advantage and complexity, online universities should examine these precursors in order to increase the current low level of usage of mobile devices for learning. In other words, advantages of mobile learning such as accessibility, portability, and reduced complexity can be enhanced by intuitive interfaces and user experience design principles relevant to the mobile technology affordances. Then learners' intention to use is likely to be facilitated, which will eventually increase the uptake of mobile learning.

Implications for further study are suggested: Firstly, the research model could be elaborated by a series of follow-up studies. For example, a possible mediating role of the intention to use between the perceived attributes of innovation and the actual use should be investigated. Also, replicated studies are required in order to confirm the non-significant effects of trialability and observability on the intention to use in the online university context. Secondly, a further study could change the research design to a comparison between two groups of learners: those who have been using mobile learning and those who have not. Also, in-depth interviews with learners from both groups may shed new light on the use of mobile learning as

an innovation for online universities. This qualitative exploration would provide administrators and instructors of online universities with robust understandings regarding the mechanism of diffusion for the mobile delivery method. Thirdly, a follow-up study could investigate specific design principles for mobile learning. This study reported complexity as one of the predictors for intention to use mobile device for learning. A next step would be to identify instructional as well as interface design aspects unique to mobile technology affordances.

Limitations for this study are as follows: First, the actual usage counted frequency only, and the length of time of each usage was not considered. It would be worth differentiating between frequency and amount of time in a follow-up study. Second, mobile learning in this study was limited to the use of mobile applications on smartphones and tablets. That is, a broader definition of mobility, which would include students accessing traditional course web sites on wireless-enabled laptops was not considered. However, laptops were intentionally excluded from this study because our focus was on mobile application usage. Third, this study was conducted with Asian online university learners. These students may have quite distinct usage profiles, and as a result it may be difficult to generalise the results of this study to other users and locations.

Acknowledgments

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Corresponding author: Kyu Yon Lim, klim@ewha.ac.kr