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Understanding the adoption of mobile-learning in South Korea: Using the integrated technology acceptance analysis*

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Abstract

This study analyzes factors that influence the continuance intention of mobile learning (m-learning) for its users. We collected 222 responses from an online survey in South Korea. We conducted an empirical analysis by integrating the technology acceptance model and psychological factors related to learning. Subsequently, we verified the hypotheses drawn in this study using confirmatory factor analysis and structural equation modelling. The results show that perceived enjoyment, connectedness, and security, respectively, had a positive effect on the perceived ease of use and perceived usefulness of learning for users. Additionally, the results showed that perceived usefulness could be improved by increasing the perceived ease of use, which had a positive influence on learning satisfaction, learning self-efficacy, and continuance intention of m-learning, which were crucial to users' learning outcomes. Particularly, learning self-efficacy, which was positively influenced by learners' learning satisfaction, was also expected to boost the use of m-learning by influencing the continuance intention of m-learning. This study provided critical clues for expanding related research, and hence, this study has important implications for academic and practical purposes.

Keywords: M-learning, technology acceptance model, perceived usefulness, learning satisfaction, learning self-efficacy

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Introduction

With the advancement of information and communications technology (ICT), mobile devices have gained importance in our daily lives (Al-Shihi & Sharma, 2018). The use of mobile devices has gained prevalence across the world and has been gaining popularity, especially among teenagers (Rau et al., 2008). In addition to their use in calling, text messaging, and Internet browsing, the use of mobile devices equipped with various applications is becoming increasingly widespread. Accordingly, manufacturers are currently developing devices that deliver high-performance user interface solutions and user experience (UI/UX) to satisfy more customers' needs.

The advancement of mobile technology and the growth in uses of mobile devices have made mobile learning (m-learning) an important element in the ICT domain and transformed learning environments (Hashim et al., 2015). For example, an increase in the ownership of mobile devices among teenage students has increased their ease of access to learning and obtaining information. Consequently, this scenario has increased the popularity of m-learning (Domingo & Gargante, 2016; Fu & Hwang, 2018; Heflin et al., 2017). Owing to m-learning, knowledge sharing and acquisition are no longer limited by space and time, such as classrooms, and hence, learning can take place anywhere and anytime according to the need for learning (Mohammadi, 2015).

M-learning is defined as e-learning that uses mobile interfaces (Kim & Ong, 2005). Also, prior studies apply a concept that views mobile learning as learners connected to a mobile resources and devices (Kim & Shin, 2015; O'Bannon & Thomas, 2015). The paradigm shift from online learning to m-learning is characterized by a transition of technical terminology. The dominant keywords in the e-learning are interactive, hyperlinked, and online media. In m-learning, terms like connected, personal, secured, and enjoyment are more salient (Park & Kim, 2014).

M-learning strengthens education systems through advancements in mobile computing, and it has been recently developed to promote interactive knowledge sharing (Al-Emran et al., 2016). With the widespread expansion of mobile devices and Internet connectivity and the decline in prices of mobile devices, m-learning is considered a key element of curricula (O'Bannon & Thomas, 2015).

Previous studies have shown that m-learning supports knowledge dissemination and meets the educational needs of students and employees in various areas, such as meeting learning outcomes (Liu et al., 2010), business goals (MacCallum et al., 2014), and information technology needs (Hamidi & Chavoshi, 2017). Therefore, research on m-learning has also become increasingly critical. Particularly, the importance of identifying factors affecting users' acceptability of m-learning has been attracting considerable attention from an academic perspective (Althunibat, 2015; Cheng, 2015; Graham et al., 2013).

Although many recent reviews highlight the positive effect of m-learning on improving learning outcomes, motivation (Crompton et al., 2017), and students' learning awareness of specific subjects, such as math and science (Hwang et al., 2018), research on why learners choose and accept m-learning remains limited (Hwang et al., 2018). As mentioned above, the influence of m-learning on mobile device-related technologies is increasing. Therefore, we conducted this study to analyze key determinants that influence the use of m-learning. We conducted an empirical analysis using the technology acceptance model (TAM) of how the factors influencing the acceptance of m-learning were determined, specifically analyzing users' psychological factors.

M-learning services and market trends

There are different views on the outlook of m-learning, but there is no dispute over its significant growth potential. Markets and Markets (2018) forecast that the m-learning market would grow from $8 billion in 2015 to $37.6 billion in 2020 at a compound annual growth rate (CAGR) of 36.3%. Metaari Advanced Learning Technology Resesarch (2020) forecasted that the m-learning market would grow at a CAGR of 12.0% over the five-year period from 2016 to 2021. Although it is assumed that this market extends into e-learning, m-learning is the second-largest market after self-study e-learning, which is one of the traditional learning methods (Cha & Kwon, 2018).

The m-learning market has been experiencing rapid global growth over the last few years. The cutting-edge technology used by the m-learning industry has been playing a crucial role in enabling students and educators to have a richer learning experience. This scenario has increased the receptiveness of educational institutions and businesses toward adopting technologies that comprise an m-learning platform (Cha & Kwon, 2018).

In Korea, the government's large-scale ICT infrastructure investment in the late 1990s and its competitive technology infrastructure for the development of m-learning support the growth and advancement of the m-learning industry (Park et al., 2014). Approximately 97.5% of all households can access broadband networks (OECD, 2016), and approximately 99% of the population can access broadband mobile communication networks. Hence, mobile traffic accounts for 37% of the total web traffic in Korea, and people find it inconvenient to live without mobile devices (Park et al., 2018).

To effectively use the mobile environment, the Korean government has launched a policy to digitize educational materials and enable students to access most educational materials through mobile platforms (Park et al., 2018). Korea is one of the most mature m-learning markets in the world, in which users can enjoy unlimited data plans at a relatively low cost (Kang et al., 2015). However, despite the fact that Korea features a rapidly growing m-learning market, research on the influence of m-learning on Korean users is still limited. Moreover, there has been no quantitative analysis of the willingness and acceptance of m-learning, both domestically and internationally.

Extracting potential determinants

To identify potential determinants that have a crucial effect on the continuance use and acceptance of m-learning services, we conducted in-depth interviews with ten academic experts who specialized in m-learning and educational technology (Park et al., 2018). After interviewing experts, based on the interview results and analysis, we identified eight variables that were included in our research model. Subsequently, we derived hypotheses and conducted an empirical analysis of the main variables.

Literature review and research hypothesis

Earlier studies on m-learning had a limited focus as they focused on the use of mobile computing devices for learning (Bano et al., 2018). However, recent studies have focused more on the convenience of learning through mobile devices, that is, mobility (Kim et al., 2017). Additionally, several studies have defined m-learning as a new learning technology that can expand digital learning channels through mobile networks and tools, and provide educational services, educational information, and educational resources anytime and anywhere (Cha & Kwon, 2018; Park & Kim, 2014).

Since users have become more open-minded, they have begun using mobile devices even for learning. In this context, it is important to indicate that, today, many researchers in academic fields have started emphasizing the need to investigate the characteristics of m-learning and conduct research on aspects that affect the m-learning acceptance of learners and educators (Al-Emran et al., 2016; Park & Kwon, 2016). Therefore, based on previous studies, we comprehensively defined m-learning as a system that is supported by a wireless ICT environment and provides learning content to anyone, anytime, and anywhere, using a mobile device such as a smartphone. We also analyzed the key factors that affected the acceptance of m-learning.

Perceived enjoyment

Since students can get bored and disconnected from educational outcomes if they learn in traditional ways, enjoyment is a very important element in today's education (Park & Kwon, 2016). Previous studies regarded student enjoyment as a crucial element affecting learning (Baek & Touati, 2017; Klimmt et al., 2007; Klimmt et al., 2009). Perceived enjoyment refers to the degree to which users (learners) perceive enjoyment in m-learning (Dishaw & Strong, 1998). As mobile devices not only improve productivity but also have elements that promote enjoyment, it should be considered a key element for users to accept m-learning (Huang et al., 2007).

Perceived enjoyment allows users to enjoy learning activities using mobile devices. This is an example of intrinsic motivation, and perceived enjoyment is known to influence user acceptance of new technologies and disciplines. Previous studies have shown that perceived enjoyment is a key factor influencing the perceived ease of use (Park & Kwon, 2016; Pramana, 2018). Additionally, according to various studies, including studies on learning systems using multi-media and web-based learning systems, enjoyment increases the ease of use for students (Shyu & Huang, 2011; Zare & Yazdanparast, 2013). Therefore, in this study, we set a hypothesis related to perceived enjoyment as follows.

H1. Perceived enjoyment has a positive effect on the perceived ease of use of m-learning.

Perceived connectedness

In a smart environment, users want to be able to use available components easily and interact with these components anytime. Learners enjoy communicating with their colleagues and sharing information mobile interface (Park & Kim, 2014). Mobile learning is an efficient tool for such interactions, which provide chances to contact with others who share diverse ideas and learning solutions (Baek & Touati, 2017; Cheng, 2015).

In this context, perceived connectedness refers to the degree to which users feel emotionally associated with the world, various resources in their environment, and people (Kwon et al., 2014; Shin, 2010). For instance, similar to online communication services (Shin & Kim, 2008), m-learning also provides users with various functions, such as operation and control. Therefore, users may feel engaged in m-learning, like in the case of other existing ICT-based services, and believe that they can easily use service elements (Park et al., 2018). In addition, mobile learning enables continued connections between learning materials and learners (Cheng, 2015). According to previous studies, perceived connectedness to ICT-based services positively affected the perceived ease of use of these services (Kwon et al., 2014; Park et al., 2017). Therefore, in this study, we set a hypothesis related to perceived connectedness as follows:

H2. Perceived connectedness has a positive effect on the perceived ease of use of m-learning.

Perceived security

Procedures and systems aim to ensure security within systems, and security is one of the main concerns in many areas related to mobile devices. While mobility, immediacy, and availability are key benefits of mobile devices, these characteristics increase concerns related to privacy and security of data stored and accessed through mobile devices (Almaiah, 2018).

Therefore, security issues related to the growth of mobile devices pose challenges for m-learning (Hamidi & Chavoshi, 2017). Access to mobile content available to users hampers security (Hao et al., 2017). Previous studies have shown that perceived security plays an important role in perceived usefulness of mobile systems and SNS (Kwon et al., 2014). Of these studies, Park et al. (2018) empirically found that perceived security had a positive effect on perceived usefulness of smart home services. Therefore, in this study, we set a hypothesis related to perceived security as follows:

H3. Perceived security has a positive effect on the perceived usefulness of m-learning.

Technology acceptance model

Of the theories related to the acceptance of new technologies and products, the technology acceptance model (TAM) is the most effective in terms of explanatory power (Davis, 1989). TAM is based on the social psychological theory that explains and interprets rational behavior (Ajzen & Fishbein, 1980). The TAM uses two key cognitive belief constructs that are essential when users accept new technologies or products in the IT field to analyze the belief-attitude-intention-behaviour relationship (purchase and use, among others). Two core constructs are the perceived ease of use and perceived usefulness (Davis, 1989).

The perceived ease of use refers to the degree to which users lack effort required in using a particular device, and perceived usefulness is defined as the degree to which users perceive the use of a particular system effective based on their performance (Davis, 1989). Prior studies show that the perceived ease of using learning materials and service tools is one of the most significant factors affecting the perceived usability of m-learning devices (Kang et al., 2015; Kim et al., 2015). According to previous studies, perceived usefulness is most directly and positively influenced by the perceived ease of use (Davis et al., 1989; Kwon et al., 2014; Park & Kwon, 2016). Based on this, we inferred the following hypothesis.

H4. Perceived ease of use has a positive effect on the perceived usefulness of m-learning.

The TAM remains one of the most actively used models in studies for analyzing aspects of how users accept information systems (IS) due to its adaptability and simplicity. Even from the perspective of m-learning, the TAM presents the most effective theory for explaining users' learning outcomes, intentions, and satisfaction (Park & Kwon, 2016). Previous studies have emphasized that learners are more satisfied and achieve higher self-efficacy in learning as they feel more perceived usefulness (Yoo & Cho, 2018).

Learning satisfaction is one of the crucial elements that must be considered to improve the learning experience. According to previous studies, learning satisfaction has an effect on learning outcomes and learning efficacy (Martirosyan et al., 2014). Additionally, it is an important factor to measure the level of learners' motivation (Kuo et al., 2014). Particularly, the more that the user perceives mobile devices to be useful, the higher will be learners' satisfaction and confidence acquired from learning (Kim & Ong, 2005; Yoo & Cho, 2018). Moreover, if users perceive new devices, such as mobile devices, to be useful, their continuance intention to use those products and devices will also increase (Kwon et al., 2014; Park et al., 2017). In previous studies, perceived usefulness was considered the most crucial factor for increasing the continuance intention of users for those products and devices (Kim et al., 2015). Based on previous studies, we derived the following hypotheses related to perceived usefulness:

H5. Perceived usefulness has a positive effect on learning satisfaction.
H6. Perceived usefulness has a positive effect on learning self-efficacy.
H7. Perceived usefulness has a positive effect on m-learning continuance intention.

Learning satisfaction and learning self-efficacy

Learning satisfaction refers to an overall satisfaction level that learners feel or experience after learning, and it is known to be a variable that has a positive effect on learners' ongoing learning progress and learning efficacy (Roca et al., 2006). Among previous studies, the studies by Shukla & Dixit (2015) and Bhaskaran & Swaminathan (2014) defined students' feelings, attitudes, and preferences during and after learning as learning satisfaction. They maintained that the confidence and efficiency of learning increased with an increase in learning satisfaction.

Learning self-efficacy can be strengthened by improved learning satisfaction, and is based on a student's personal beliefs in learning outcomes and performance (Schunk, 1989). These beliefs have an influence on how people feel, think, motivate themselves, and behave (Menekse et al. 2018). Particularly, learning self-efficacy in a mobile environment is defined as the degree of confidence of individuals to perform their intended tasks or the degree of understanding required to use mobile devices (Park, 2009; Taylor & Todd, 1995). Learning self-efficacy has been drawing attention as a factor that influences acceptance intention. Results of the causal relationship between learning self-efficacy and acceptance intention have shown that enhanced learning self-efficacy had a positive effect on acceptance intention (Gbenga et al., 2013; MacCallum et al., 2014).

Particularly, in a learning environment based on new technologies, such as ICT-based education and m-learning, previous studies have confirmed that self-efficacy related to learning was influenced by learning satisfaction. Consequently, it may have a significant effect on learners' intention to use m-learning in the future (Liaw & Huang, 2013). Additionally, Liaw & Huang (2013) and Pramana (2018) emphasized that self-efficacy had a direct effect on the intention to use, learning satisfaction, and perceived usefulness. Therefore, in this study, we set hypotheses as follows:

H8. Learning satisfaction has a positive effect on learning self-efficacy.
H9. Learning self-efficacy has a positive effect on m-learning continuance intention.

Research model

This study introduced an integrated model of research, which extended the original TAM based on the hypotheses presented above (Figure 1).

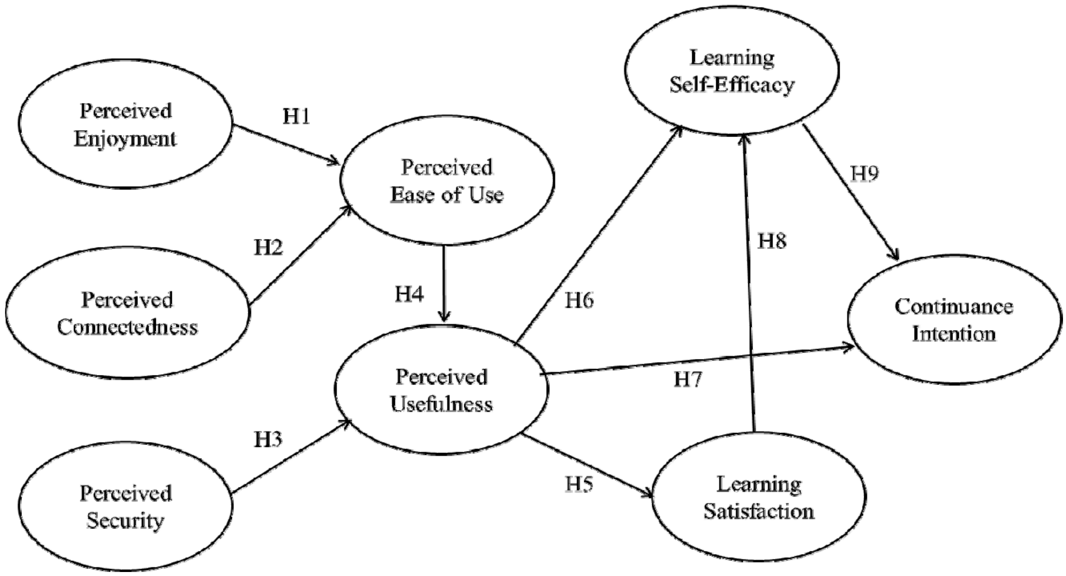

Figure 1. Research model

Method

Data collection

In this study, to verify users' continuance intention to use m-learning, we conducted a survey to analyze how users prefer and adopt m-learning. Three professors who majored in m-learning, communication, and information technology reviewed and revised the collected measurements. After the review process, an online survey was conducted with subjects with more than three-month experience with m-learning services. We conducted an online survey in collaboration with a professional online survey institution in Korea. A total of 341 copies were distributed, and 222 people responded with valid answers. Our focus on current users is attributed to the fact that only users with an experience of m-learning can accurately confirm the intention to use m-learning and the characteristics of related variables. There were more male survey respondents than females, and 76.6% of respondents were college graduates. However, respondents were evenly distributed in terms of the duration of m-learning use, which indicated that overall, respondents had a high understanding and rich experience of m-learning. The demographic characteristics of survey respondents are shown in Table 1.

Table 1. Sample demographics (*N* = 222)

Demographic factors	Classification	Number of people	%
Gender	Male	141	63.5
	Female	81	36.5
Age	20-29	67	30.1
	30-39	110	49.6
	40-49	34	15.3
	Above 50	11	5.0
Education	High school or below	31	14.0
	College	170	76.6
	Graduate or Above	21	9.4
Usage period	3 months below	41	18.5
	3-6 months	56	25.2
	6-12 months	45	20.3
	12-24 months	39	17.5
	More than 24 months	41	18.5

Measurements

We composed a survey questionnaire by considering previous studies as well as variables of the TAM. All measurement questions in English were translated and modified into Korean equivalents. A translator and an expert in this field helped and supported this survey. Additionally, measurement questions were finalized through review and revision by experts in education, psychology, and communication fields. The final measurement questions used in this study are presented in Table 2. All items were measured on a 5-point Likert scale (1 = “Strongly disagree” – 5 = “Strongly agree”).

Table 2. Instruments

Factors	Items	Explanations	References
Perceived enjoyment	PE1	Using m-learning services is fun.	(Kim et al., 2013)
	PE2	M-learning services are interesting.	
	PE3	Using m-learning services is pleasant.	
Perceived connectedness	PC1	I feel good because I can access m-learning services anytime.	(Park & Kim, 2014)
	PC2	I feel like being connected to the m-learning services because I can avail any information on the services' components.	
	PC3	I feel comfortable because I can interact with the components via m-learning services.	
Perceived security	PS1	M-learning services ensure the safety of my personal information.	(Hartono et al., 2014)
	PS2	I think my information on m-learning platforms will not be manipulated.	
	PS3	I think that nobody can see and use my information stored in m-learning services.	
Perceived ease of use	PEU1	I do not find the use of m-learning services difficult.	(Kim & Shin, 2015)
	PEU2	My interaction with m-learning services is clear.	
	PEU3	Interacting with m-learning services does not require any mental effort.	
Perceived usefulness	PU1	Using m-learning services improves my competency.	(Kwon et al., 2014)
	PU2	Using m-learning services helps me to accomplish my tasks at a rapid pace.	
	PU3	I have found m-learning services to be very useful.	
Learning satisfaction	LS1	I like the idea of learning through a mobile interface.	(Hu & Hui, 2012)
	LS2	Overall, I am satisfied with m-learning services.	
	LS3	My learning experience through the mobile interface has been positive.	
	LS4	Acquiring knowledge through the mobile interface is enjoyable.	
Learning self-efficacy	LSE1	I feel confident using m-learning services to learn about and apply concepts.	(Santhanam et al., 2008)
	LSE2	Using m-learning services has helped me to learn things efficiently	
	LSE3	I would be comfortable using m-learning services.	
	LSE4	I could apply concepts that I learned from m-learning services.	
M-Learning continuance intention	MCI1	I intend to continue using m-learning services for my learning in the future.	(Venkatesh et al., 2012)
	MCI2	I will always try to use m-learning services for my daily learning activities.	
	MCI3	I plan to continue to use m-learning services for my learning frequently.	

Results

Descriptive analyses and measurement validity

In this study, we first conducted a confirmatory factor analysis (CFA) using AMOS 18.0 and SPSS 18.0 to verify the hypotheses. We obtained the descriptive information of variables based on the survey data. Subsequently, we conducted an analysis based on the guidelines emphasized in previous studies to verify whether the variables of measurement questions had reliability and validity. According to previous studies, by using structural equation modeling (SEM) and CFA, the number of samples should be equal to or greater than 200, and composite reliability and Cronbach alpha values should be equal to or greater than 0.7. Additionally, both factor loading and item-total correlation should also be equal to or greater than 0.6 to secure the reliability and validity of the measured variables. Finally, the value of the average variance extracted (AVE) should be equal to or greater than 0.5 (Anderson & Gerbing, 1988; Hair et al., 2006). The measurement questions used in this study were confirmed to secure the reliability and validity of the variables, going beyond the guidelines emphasized in previous studies. The descriptive statistics, validity, and reliability of the main constructs used in this study are presented in Tables 3 and 4.

Table 3. Mean and standard deviation of constructs

Construct	Mean	*SD*	Construct	Mean	*SD*
Perceived enjoyment	3.29	0.68	Perceived usefulness	3.48	0.86
Perceived connectedness	3.47	0.69	Learning satisfaction	3.61	0.80
Perceived security	3.60	0.74	Learning self-efficacy	3.52	0.76
Perceived ease of use	3.48	0.80	Continuance intention	3.23	0.79

Table 4. Internal and convergent validity test

Factor	Item	Internal reliability		Convergent reliability		
		Cronbach's alpha	Item-total correlation	Factor loading	Composite reliability	Average variance extracted
Perceived enjoyment	PE1	0.732	0.734	0.712	0.830	0.622
	PE2		0.861	0.887		
	PE3		0.655	0.834		
Perceived connectedness	PC1	0.808	0.694	0.850	0.867	0.687
	PC2		0.769	0.873		
	PC3		0.824	0.832		
Perceived security	PS1	0.794	0.677	0.882	0.827	0.615
	PS2		0.786	0.824		
	PS3		0.767	0.821		
Perceived ease of use	PEU1	0.867	0.818	0.882	0.887	0.723
	PEU2		0.816	0.892		
	PEU3		0.843	0.892		
Perceived usefulness	PU1	0.908	0.848	0.917	0.908	0.768
	PU2		0.867	0.936		
	PU3		0.867	0.904		
Learning satisfaction	LS1	0.880	0.757	0.820	0.895	0.680
	LS2		0.850	0.881		
	LS3		0.801	0.854		
	LS4		0.810	0.874		
Learning self-efficacy	LSE1	0.868	0.712	0.800	0.897	0.689
	LSE2		0.884	0.904		
	LSE3		0.913	0.916		
	LSE4		0.682	0.772		
Continuance intention	MCI1	0.897	0.913	0.935	0.927	0.810
	MCI2		0.912	0.926		
	MCI3		0.772	0.872		

Measurement and research models

Both the measurement and research models of this study were found to have validity and reliability. As shown in Table 5, the goodness-of-fit index (GFI), adjusted goodness-of-fit (AGFI), root mean square error of approximation (RMSEA), normed fit index (NFI), comparative fit index (CFI), and incremental fit index (IFI) all satisfied the guidelines emphasized in previous studies; hence, both the measurement and research models were supported. In addition, the chi-square test also yielded values of less than 5.00. For reference, previous studies emphasized that the value of the chi-square test decreases slightly as the number of survey samples required for research becomes greater than or equal to 200 (Hair et al., 2006). Overall, this study confirms validity through all tests conducted.

Table 5. Fit indices of measurement and research models

Fit indices	Measurement model	Research model	Recommended value	References
GFI	0.885	0.905	> 0.900	(Bentler & Bonett, 1989)
AGFI	0.903	0.904	> 0.900	(Hair et al., 2006)
RMSEA	0.040	0.045	< 0.080	(Seyal et al., 2002)
NFI	0.803	0.805	> 0.800	
CFI	0.913	0.913	> 0.900	
IFI	0.915	0.915	> 0.900	
x2/d.f	4.132	4.151	< 5.000	

Discriminant validity

For the analysis of discriminant validity, we additionally compared the correlation values between the main constructs with the values of the square root of the AVE of each construct. The results show that the study's model has discriminant validity, as the value of the square root of AVE of each construct is greater than the correlation values between constructs. Table 6 shows that the value of the square root of AVE of each construct is greater than the correlation value between each construct, which confirms that the study model has discriminant validity.

Table 6. Discriminant validity test with AVE

	1	2	3	4	5	6	7	8
1. Perceived enjoyment	0.789							
2. Perceived connectedness	0.643	0.829						
3. Perceived security	0.510	0.561	0.784					
4. Perceived ease of use	0.599	0.608	0.513	0.850				
5. Perceived usefulness	0.601	0.583	0.278	0.589	0.876			
6. Learning satisfaction	0.333	0.444	0.570	0.328	0.484	0.825		
7. Learning self-efficacy	0.448	0.483	0.591	0.409	0.495	0.701	0.830	
8. Continuance intention	0.633	0.686	0.486	0.694	0.562	0.304	0.384	0.900

Hypothesis testing

The validation results of the hypotheses of this study are shown in Table 7 and Figure 2. The results of the empirical analysis show that all hypotheses are supported. Perceived enjoyment (H1, b = 0.422, CR = 5.405, $p < .001$) and perceived connectedness (H2, b = 0.446, CR = 5.810, $p < .001$) have a positive effect on the perceived ease of use of m-learning. In addition, the perceived security (H3, b = 0.670, CR = 12.381, $p < .001$) and perceived ease of use (H4, b = 0.312, CR = 6.258, $p < .001$) have a meaningful positive effect on perceived usefulness. As a result, perceived usefulness has a meaningful positive effect on learning satisfaction (H5, b = 0.451, CR = 8.054, $p < .001$), learning self-efficacy (H6, b = 0.181, CR = 3.779, $p < .001$), and continuance intention (H7, b = 0.450, CR = 7.650, $p < .001$) of users. However, learning satisfaction influenced by perceived usefulness has a positive effect on learners' learning self-efficacy (H8, b = 0.575, CR = 11.357, $p < .001$) (H9, b = 0.144, CR = 2.203, $p < .01$), and learners' learning self-efficacy enhanced by learner's learning satisfaction has a positive effect on learner's continuance intention to use m-learning.

These results indicate that these elements play a crucial role in increasing learner's continuance intention to use m-learning. In other words, learning enjoyment and connectedness contributed to increasing the perceived ease of use of m-learning, and the transparency and the ease of use through perceived security contributed toward increasing the perceived usefulness of m-learning. Perceived usefulness is the most important factor in increasing learner's learning satisfaction, learning efficacy, and continuance intention to use m-learning. Learners' learning self-efficacy, which is improved due to learning satisfaction, increases the continuance intention of learners to use m-learning.

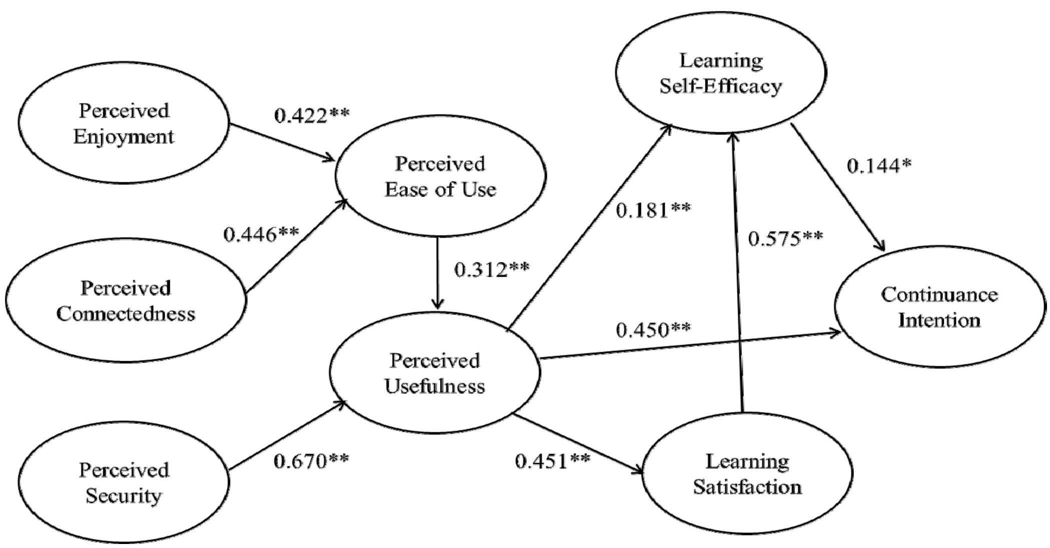

Figure 2. Summary of the research model (*$p < 0.05$, **$p < 0.001$)

Table 7. Results of hypothesis tests

Hypothesis	Standardized coefficient	*SE*	CR	Supported
H1. Perceived enjoyment → Perceived ease of use	0.422**	0.078	5.405	Supported
H2. Perceived connectedness → Perceived ease of use	0.446**	0.077	5.810	Supported
H3. Perceived security → Perceived usefulness	0.670**	0.054	12.381	Supported
H4. Perceived ease of use → Perceived usefulness	0.312**	0.050	6.258	Supported
H5. Perceived usefulness → Learning satisfaction	0.451**	0.056	8.054	Supported
H6. Perceived usefulness → Learning self-efficacy	0.181**	0.048	3.779	Supported
H7. Perceived usefulness → Continuance intention	0.450**	0.059	7.650	Supported
H8. Learning satisfaction → Learning self-efficacy	0.575**	0.051	11.357	Supported
H9. Learning self-efficacy → Continuance intention	0.144*	0.065	2.203	Supported

Discussion and conclusion

In this study, we empirically analyzed the determinants of learners' intention to use m-learning by integrating psychological factors, such as learning satisfaction and learning self-efficacy, based on the TAM. Study results show that learners' perceived usefulness and learning self-efficacy are the most critical factors that influence their continuance intention to use m-learning. In addition, this study suggests that learning enjoyment must be considered to increase learners' perceived ease of use and perceived usefulness. Additionally, the study suggests that connectedness and security should be strengthened in terms of m-learning intention. Based on the study results, we were able to derive the following academic contributions and practical implications.

First, from an academic perspective, this study contributed to confirming the continuance intention to use newly emerging m-learning solutions by integrating learning satisfaction and learning-self efficacy—the psychological factors of m-learning users based on the TAM framework. Most previous studies analyzed the aspects of how learners accept e-learning (Cha & Kwon, 2018; Liaw & Huang, 2013). However, this study comprehensively analyzed not only the TAM model that was most widely used to identify intention to use new devices and media, but also satisfaction and self-efficacy, among others, that were most directly related to learners' learning outcomes and intentions. It thereby expands the existing TAM research area into m-learning.

Second, this study suggested new academic implications by changing the viewpoint of the existing research, which focused only on the achievement and innovation of m-learning. This study contributed to the existing literature by focusing on the intention to use m-learning. Existing research provided only a result-oriented viewpoint that m-learning had a positive effect on learners' performance improvement (Kim et al., 2017; Rau et al., 2008). However, this study focused on the intention of how users utilize m-learning more than learning achievement. This study suggested the following implications for further research on m-learning. The combination of learning enjoyment, connectedness, and security of m-learning systems can improve the perceived usefulness of m-learning, improve learning satisfaction and learning self-efficacy, and thereby improve the intention to use m-learning.

From a practical perspective, this study provided important clues on how companies and educational policy institutes developing m-learning platforms should develop learning structures and systems. M-learning should be simple and easy to access. However, it should provide student enjoyment, system security, and connectedness at all times. M-learning is not as active as e-learning. This is partly due to frequent Wi-Fi outages and the lack of system stability. Entrepreneurs and educational policy organizations that have already entered or will participate in the m-learning contexts should take into consideration these points and emphasize the stable operation of both the content and system of m-learning.

However, this study also has the following limitations, and thus subsequent studies should address these shortcomings to realize more effective conclusions. First, the data in this study was collected only in South Korea, and thus the study's results cannot be generalized to other contexts. The development speed and expansion direction of m-learning and user patterns differ across regions. Therefore, based on the results of this study, we should conduct a comparative study between countries or between cultures to identify the intention to use m-learning in each country.

Second, this study did not consider the individual characteristics of learners. This study did not reveal the tendencies of users who were more likely to use m-learning and characteristics of users who were more likely to have the intention to use m-learning. If research results are presented by differentiating the patterns of m-learning based on user characteristics, values, and tendencies, then we can provide richer academic contributions and practical implications. We will conduct subsequent studies by taking these points into consideration.

Third, this study did not examine the effect of perceived cost, that is, the economic value of m-learning. Previous studies related to the TAM divided perceived cost into perceived enjoyment (hedonic value), perceived connectedness (comfortable value), and perceived security (security value), and, subsequently, analyzed how these values increased the intention to use new products or devices (Park et al., 2018; Park & Kwon, 2016). In this study, we analyzed existing studies in detail and drew conclusions by empirically analyzing how these values influenced the continuance intention to use m-learning. However, we did not analyze the influence of perceived cost, which is an economic consideration. Since users who learn through m-learning are sensitive to cost, in subsequent studies, we must analyze how perceived cost influences their intention to use m-learning.

M-learning is expected to grow exponentially in the future. Therefore, research on m-learning will continue to expand. This study has contributed to the study and practice of m-learning by integrating the TAM and m-learning users' psychological factors, and empirically analyzing the relationships between these factors. In subsequent studies, we will conduct research on the outcomes and innovation patterns of m-learning from various perspectives by including additional variables.

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