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A Model Predicting Student Engagement and Intention with Mobile Learning Management Systems

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Abstract

Aim/Purpose	The aim of this study is to develop and evaluate a comprehensive model that predicts students' engagement with and intent to continue using mobile-Learning Management Systems (m-LMS).
Background	m-LMS are increasingly popular tools for delivering course content in higher education. Understanding the factors that affect student engagement and continuance intention can help educational institutions to develop more effective and user-friendly m-LMS platforms.
Methodology	Participants with prior experience with m-LMS were employed to develop and evaluate the proposed model that draws on the Technology Acceptance Model (TAM), Task-Technology Fit (TTF), and other related models. Partial Least Squares-Structural Equation Modeling (PLS-SEM) was used to evaluate the model.

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Contribution	The study provides a comprehensive model that takes into account a variety of factors affecting engagement and continuance intention and has a strong predictive capability.
Findings	The results of the study provide evidence for the strong predictive capability of the proposed model and support previous research. The model identifies perceived usefulness, perceived ease of use, interactivity, compatibility, enjoyment, and social influence as factors that significantly influence student engagement and continuance intention.
Recommendations for Practitioners	The findings of this study can help educational institutions to effectively meet the needs of students for interactive, effective, and user-friendly m-LMS platforms.
Recommendations for Researchers	This study highlights the importance of understanding the antecedents of students' engagement with m-LMS. Future research should be conducted to test the proposed model in different contexts and with different populations to further validate its applicability.
Impact on Society	The engagement model can help educational institutions to understand how to improve student engagement and continuance intention with m-LMS, ultimately leading to more effective and efficient mobile learning.
Future Research	Additional research should be conducted to test the proposed model in different contexts and with different populations to further validate its applicability.

Keywords	engagement, continuance intention, m-LMS, TAM, TTF, perceived usefulness, perceived ease of use, interactivity, compatibility, enjoyment, social influence

INTRODUCTION

The sudden outbreak of COVID-19 led to widespread closures of universities, necessitating a shift towards online and mobile learning (m-learning) for millions of higher education students. Higher education institutions had to quickly adopt these technologies to continue delivering education to students, and it is likely that these technologies will continue to play an important role in the post-pandemic era (Lacka et al., 2021).

Institutions began to incorporate m-learning as a means of engaging students and meeting their needs (Martinovic et al., 2010). M-learning is facilitated by the ubiquity and intelligent user interfaces of mobile devices (Sharma & Kitchens, 2004). Mobile-based Learning Management Systems (m-LMS) have the potential to influence academic achievement (Han & Shin, 2016) and support instructors in providing asynchronous learning materials (Raza et al., 2021). However, there has been limited investigation of the determinants and consequences of engagement with m-LMS.

Engagement in mobile-based learning (m-learning) is a critical factor that has been the focus of research in the last decade. It is well-established in the literature that many students have struggled to maintain motivation and engagement during online learning (Chiu, 2022; Li & Lalani, 2020; Martin & Bolliger, 2018). In addition, instructors have less control over how students engage with the material in these environments when compared to traditional in-person classroom settings (Han & Shin, 2016). This lack of control and engagement can lead to a decrease in student motivation and interest in the material, which can ultimately affect their performance and learning outcomes.

Given these challenges, it is crucial for researchers to investigate the factors that affect engagement with m-LMS in higher education. This research can help educators understand how to create effective and engaging m-learning environments for students. Additionally, research can help educators identify strategies for increasing student engagement with m-LMS and create more effective and engaging m-learning environments that can lead to improved learning outcomes for students.

Online LMS is a valuable tool for educational institutions, such as universities, to engage and interact with students in a convenient and effective manner (Momani & Abualkishik, 2014). However, despite their benefits, LMS faces several challenges that may affect their adoption and usage in universities, such as technical difficulties, lack of faculty training, student resistance, cost, and compatibility issues. One potential solution to these challenges is employing modern technologies, such as mobile devices, to facilitate the use of LMS, and make them more convenient for students and instructors to access and utilize.

Although m-LMS have the potential to improve student engagement in higher education, there is currently no research that has explored their impact on this outcome. While there are studies that have investigated the impact of traditional LMS on student engagement, there is a need for further research to examine the unique features and affordances of mobile platforms in fostering student engagement. This lack of research may discourage universities from relying on m-LMS as a primary tool for interaction and engagement with students. Consequently, higher education institutions rely mostly on traditional LMS rather than m-LMS (Almasri, 2015). Han and Shin (2016) also found that the limited studies conducted on the impact of m-LMS on student engagement in higher education might be a discouraging factor for universities to adopt m-LMS. In order to increase the acceptance and usage of m-LMS, more research is needed to explore their impact on student engagement and to understand how they can be used effectively in higher education.

In the field of higher education, there has been a variety of models developed to predict the acceptance of learning technologies, such as the TAM, and Information Systems Success Model (ISSM). These models have been widely used in studies to understand the factors that influence the acceptance of learning technologies among students and instructors (Arpaci, 2019). However, as research in this area has progressed, new factors have been identified and incorporated into these models to enhance their predictive power.

TAM is one of the most widely used models to predict the acceptance of learning technologies in higher education. It posits that perceived usefulness and perceived ease of use are the key determinants of a user's intention to use technologies. Similarly, the ISSM has undergone development with the addition of new factors. Originally, the ISSM model was developed with the belief that system quality, information quality, and service quality are the main predictors of system success. However, as research in this area has progressed, new factors such as user satisfaction, user involvement, and user training have been added to the model to enhance its predictive power.

The current study is focused on understanding the factors that influence students' engagement with m-LMS and their intent to continue using these tools. The study is motivated by the fact that, while past research has demonstrated that students' intention to continue using m-LMS can improve educational achievement (Han & Shin, 2016), adopting and investing in these tools require large resources and infrastructure (Raza et al., 2021) and thus it is important to gain knowledge about students' usage intentions before implementation (Saroia & Gao, 2019).

The objective of this study is to gain a comprehensive understanding of the factors that influence engagement and continuance intention with m-LMS. To achieve this objective, the study employs a multifaceted approach by integrating three recognized theories – the Technology Acceptance Model (TAM), the Task-Technology Fit (TTF) model, and a model proposed by Mokhtar et al. (2018) – to construct a unified model that captures the range of determinants that affect engagement and continuance intention.

Furthermore, the proposed antecedents in the study are categorized into three distinct groups: m-LMS factors, students' factors, and social factors. The m-LMS factors include TTF, compatibility, and convenience, which refer to the extent to which the m-LMS is aligned with the task and the ease of access and use of the system. The students' factors include enjoyment, personal innovativeness, and self-efficacy, which refer to the affective and cognitive dimensions of the students' experience with m-LMS. Lastly, the social factor and social influence refer to the impact of others on the students' engagement and continuance intention with the m-LMS. This holistic approach allows for a more in-depth examination of the factors that influence engagement and continuance intention with m-LMS and can provide valuable insights for educators and practitioners.

LITERATURE REVIEW

M-LEARNING AND M-LMS

M-learning is a type of learning that leverages the capabilities of mobile devices, such as ubiquitous communication, to facilitate learning activities. Mukminin et al. (2020) define it as a distinct approach to e-learning, which differs in terms of the devices used to access the content and the learning activities. While e-learning typically relies on desktop computers or laptops, m-learning emphasizes the use of mobile devices, such as smartphones or tablets (Akour, 2010). Research studies by Saroia and Gao (2019) and Joo et al. (2016) have found that students' engagement in m-LMS has a positive impact on the success of m-LMS. However, prior research has primarily focused on students' engagement in e-learning systems rather than in m-LMS.

Previous research has highlighted that students do not need to be physically located to access web-based Learning Management Systems (LMS) (Kinash et al., 2012; Kukulska-Hulme, 2012). Instead, m-LMS provides easier accessibility by the students to the learning materials.

An increasing number of learners are utilizing their mobile devices to access their university's LMS (Martin & Ertzberger, 2013). Sarrab et al. (2012) have identified various reasons for this trend, such as availability, convenience, ubiquity, and the ability to personalize learning. Therefore, universities are shifting from e-learning to m-learning (Crompton & Burke, 2018).

Klaßen et al. (2013) have investigated various aspects of m-learning integration with LMS to enhance students' engagement. Research has also looked at usability considerations and measurements for m-LMS (Ivanc et al., 2012), students' usage of m-LMS (Hu et al., 2016), and how m-LMS quality factors differ from web-based LMS quality factors in their impact on students (Cho et al., 2014). Therefore, further investigation is still needed to understand the aspects of students' engagement with m-LMS.

TASK TECHNOLOGY FIT (TTF)

Task-technology fit describes how technology can assist users in meeting their needs and completing their tasks (Lu & Yang, 2014). The TTF model is commonly used to predict the adoption of information systems, as proposed by Aljukhadar et al. (2014). The model assesses how technology improves performance by determining the alignment between technology features and task requirements. This alignment determines the degree of task-technology fit.

Lu and Yang (2014) have revised the TTF model by incorporating social elements to understand the users' intentions to use social networking sites. D. Y. Lee and Lehto (2013) suggest that the TAM can explain users' intentions to use an information system, but it does not take into account whether the system can actually support task performance, which TTF does address. Therefore, previous research has suggested that employing TAM and TTF models together can provide a more comprehensive explanation of Information Systems (IS) adoption (Wu & Chen, 2017).

The original TTF model (Figure 1) as presented by Strong et al. (2006) consists of four factors: task characteristics, technology characteristics, task-technology fit, and technology utilization (Tam & Oliveira, 2016). The task characteristics and technology characteristics affect the task-technology fit, which in turn impacts technology utilization.

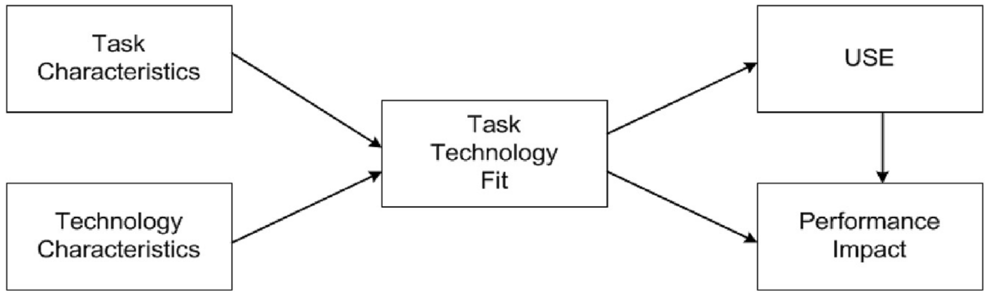

Figure 1. TTF model

The impact of engagement in e-learning and m-learning has also been studied in previous research. Blasco-Arcas et al. (2013) found that student engagement in active collaborative learning within a social web-based environment improves their learning performance. Similarly, Shao and Chen (2020) discovered that engagement has a positive impact on students' continued usage intentions for Massive open online courses (MOOCs).

RESEARCH MODEL

The current study aims to construct a model that assesses the engagement of higher education students in m-LMS and their intentions to continue using these systems in the future. The research model incorporates factors from the m-LMS, as well as personal and social factors. Figure 2 demonstrates the proposed research model.

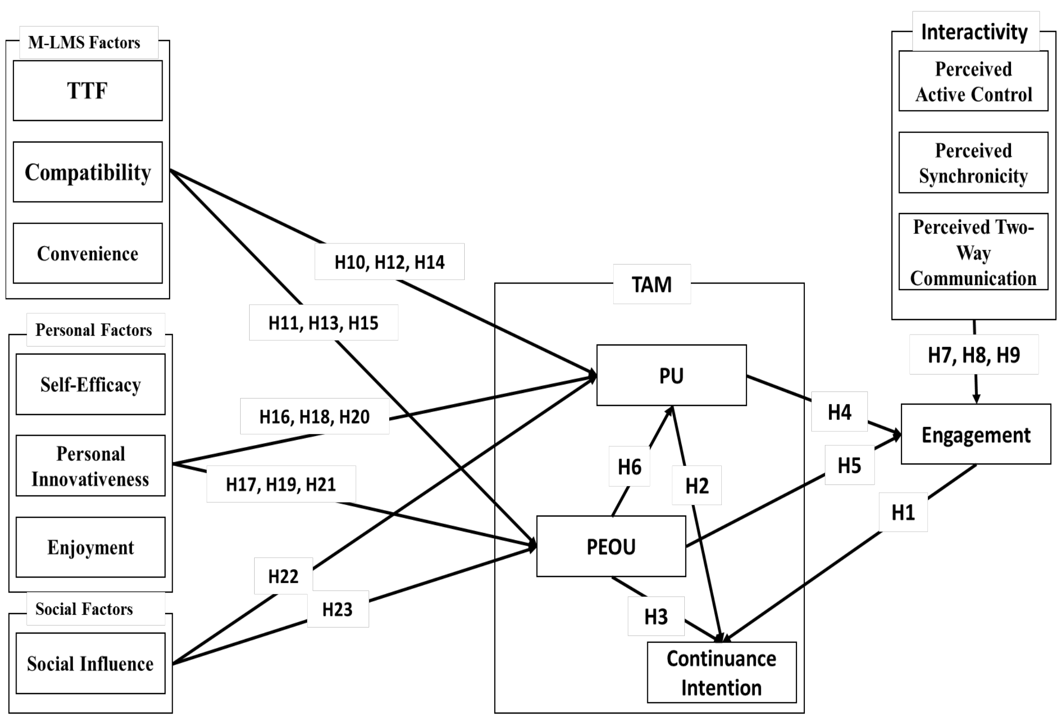

Figure 2. The research model

ENGAGEMENT IN M-LMS AND CONTINUANCE INTENTION

Engagement is the state of holding a user's attention and providing intrinsic rewards (Webster & Ahuja, 2006), and engagement in m-LMS refers to the students' emotional investment in the m-LMS (Blasco-Arcas et al., 2013). According to Shao and Chen (2020), students' engagement in LMS is the result of interactions with other students, with the instructor, and with the features provided by the online learning platform. Previous studies have shown that engagement in information systems affects future usage behavior. Fan et al. (2017) found that individuals' engagement in information systems affects their future usage behavior. Engaged students are more dedicated to the online course and m-learning and interacting with other participants.

The impact of engagement on behavioral intentions is supported by prior research (Pan, 2020). Fan et al. (2017) reported that engagement in information systems is a strong indicator of information systems dependence. Blasco-Arcas et al. (2013) investigated the impact of using clickers, which are small, handheld devices that students use to respond to questions or participate in classroom polls, on factors such as interactivity, active collaborative learning, and engagement in the classroom. Shiau and Luo (2013) confirmed that user involvement in the technology improves perceived enjoyment, satisfaction, and intention to reuse the technology. Finally, Shao and Chen (2020) argued that engaged students would continue using LMS in the future. Therefore, this study will be based on the following hypothesis:

H1: Students' engagement in m-LMS positively influences their intentions to continue using these systems in the future.

TAM AND ENGAGEMENT

TAM, introduced by Davis in 1989, was built based on the theory of reasoned action (TRA). The model proposes that users' attitudes towards an information system determine their intention to use it and their intention, in turn, determines their actual use of the IS. TAM posits that users' attitudes towards using an IS are determined by two key constructs: Perceived Usefulness (PU), and Perceived Ease of Use (PEOU). PU is the extent to which a person believes that using a technology will enhance their job performance, while PEOU is the degree to which a person perceives that using a particular system would be effortless (Davis, 1989). TAM was adopted in numerous IS adoption research. Some studies suggested modifications to TAM, typically by adding new factors to the constructs of PU and PEOU (Mokhtar et al., 2018). Other studies have confirmed the model's effectiveness in predicting users' intentions to adopt different information systems (Han & Shin, 2016; Hwang et al., 2016; Jin, 2014). Some other studies have shown that when students perceive m-learning to be useful and easy-to-use, they are more likely to be engaged in the learning process (Al-Adwan et al., 2021; Al-Emran et al., 2021; Rabaa'i et al., 2021). Therefore, this study is based on the following hypotheses:

H4: PU positively influences students' engagement in m-LMS.

H5: PEOU positively influences students' engagement in m-LMS.

Similarly, the following hypotheses were adopted from the original TAM theory:

H2: PU positively influences students' intentions to continue using m-LMS.

H3: PEOU positively influences students' intentions to continue using m-LMS.

H6. PEOU positively influences PU of m-LMS as perceived by students.

INTERACTIVITY AND ENGAGEMENT

Interactivity is a significant aspect of human-computer interaction research. m-LMS should facilitate interactive communication between students, instructors, and the m-learning platform (Fan et al., 2017). Interactivity has been defined by Liu (2003) in terms of active control, synchronicity, and two-way communication. Moreover, Fan et al. (2017) have stated that the dimensions of interactivity should be examined in order to comprehend its impact. ERP usability, which is related to interactivity, was proved to influence the intentions to continue using ERP systems (Scholtz et al., 2016). Moreover, system interactivity significantly influences students' satisfaction with Moodle (Rabaa'i et al., 2021).

Perceived active control

Perceived Active Control (PAC) describes "a user's ability to voluntarily participate in and instrumentally influence a communication" (Liu, 2003, p. 3). Research by Tan et al. (2018) has linked PAC to a user's ability to control interactive contact with other users. PAC also describes students' perception that they can freely manage their online learning schedules based on their own needs (Shao & Chen, 2020). The personalized learning experience and organizing learning schedules based on the students' habits can increase their control over their learning experience in m-LMS.

PAC positively influences behavioral intentions to adopt an information system (T. Lee, 2005; Tan et al., 2018) and positively influences user engagement in health websites (Imlawi, 2017). Perceived control over a website might affect the trust in the website. A study by Alalwan et al. (2020) also revealed that online shoppers' perceived control on a mobile shopping platform positively influences their engagement in the platform.

Research conducted by Jiang et al. (2010) has confirmed that Perceived Active Control positively influences Affinity and Affective involvement, and user engagement. The flexibility in making choices also influences user engagement (Fan et al., 2017). Therefore, it is hypothesized that:

> **H7: The Perceived Active Control of students in m-LMS positively influences students' engagement with the m-LMS.**

Perceived synchronicity

Synchronicity, as defined by Liu (2003), is the real-time and swift response to users' questions and information requests. Previous research has linked synchronicity to the speed of response in communication events. Synchronicity is related to the support provided by the m-LMS for the interaction between students and instructors (Shao et al., 2017). In traditional learning environments, students receive immediate responses to their inquiries. Thus, it is essential that m-LMS provide students with timely responses and updated content to keep them engaged.

Research by Alalwan et al. (2020) has established that the response time to users' questions influences the quality of the communication process and indirectly influences user satisfaction. The response time of a system also affects PU and PEOU (M. Li et al., 2012; Y. Li et al., 2012). Yang and Lee (2017) found that synchronicity affects enjoyment. Additionally, responsiveness has been found to influence users' engagement with an information system as per the research of Fan et al. (2017). Imlawi (2017) also found a positive influence of synchronicity on users' engagement in health websites. Alalwan et al. (2020) confirmed that synchronicity affects user engagement in mobile shopping. The synchronicity of Massive Open Online Courses (MOOCs) positively affects students' engagement in the platform as per research by Shao and Chen (2020). Therefore, it is hypothesized that:

> **H8: Perceived Synchronicity of m-LMS positively influences students' engagement with the m-LMS.**

Perceived two-way communication

Two-way communication, also known as reciprocity, is related to a system's ability to provide reciprocal communication between the system and its users (Liu, 2003). It is also related to the support provided to the communication between students and instructors (Shao et al., 2017).

Perceived communication through technology positively influences user engagement (Fan et al., 2017). Websites with reciprocal communication have been found to influence affective engagement (Jiang et al., 2010) and trust and satisfaction (Mero, 2018). Shao and Chen (2020) have confirmed the impact of two-way communication on student engagement in Massive Open Online Courses (MOOCs) platforms. Therefore, it is hypothesized that:

> **H9: Perceived two-way communication in m-LMS positively influences students' engagement with the m-LMS.**

M-LMS Features

Task technology fit (TTF)

The TTF theory, introduced by Goodhue (1995), posits that information systems are more likely to positively affect users' performance when there is a match between the IS capabilities and the task's needs. The theory takes into account system characteristics and task characteristics as predictors of TTF. Tam and Oliveira (2016) have shown that users will use technology when it helps them achieve the task in question.

The TTF theory has been used in prior research to investigate the effective adoption of mobile technologies (C. C. Lee et al., 2007). It has also been applied in studying the impact of performance in higher education for social network applications (Alamri et al., 2020), as well as in multimedia adoption behavior for learning (Park et al., 2019). However, the TTF model is parsimony in nature and does not consider the users' perceptions. This has led researchers to mostly integrate TTF with other models (El Said, 2015).

Prior studies have confirmed the impact of TTF on PU and PEOU. Wu and Chen (2017) found that TTF has an impact on PU and PEOU in Massive Open Online Courses (MOOCs). Vanduhe et al. (2020) reported similar findings regarding TTF's impact on PU and PEOU in gamification used for training in higher education. Tam and Oliveira (2016) discovered that TTF has an impact on the actual use of mobile banking. Pal and Patra (2021) also confirmed that TTF has an impact on PU and PEOU of video-based learning during the COVID-19 pandemic. Based on these findings, it is hypothesized that TTF has a significant impact on PU and PEOU.

H10: The TTF positively influences the PU of the m-LMS.

H11: The TTF positively influences the PEOU of the m-LMS.

Compatibility

Compatibility, as described by Rogers (1995, p. 15) is "the degree to which an innovation is perceived as consistent with existing values, past experiences, and the needs of potential adopters". Compatibility is one of the predictors of innovation diffusion (Rogers, 2010).

Research has confirmed the impact of compatibility on PU and PEOU (Jin, 2014; Purnomo & Lee, 2013; Rahmi et al., 2018). Compatibility has been shown to affect the PU of online courses (Tung & Chang, 2008), PU of mobile learning (Cheng, 2015), and PU of distance learning systems (Rahmi et al., 2021). Additionally, compatibility has been shown to affect the PEOU of mobile learning (Cheng, 2015), PEOU of online learning platforms (Purnomo & Lee, 2013), PEOU of collaborative learning technologies (Cheung & Vogel, 2013), and PEOU of e-books (Jin, 2014). Therefore, it is expected that compatibility of m-LMS will positively affect students' PU and PEOU. Therefore, it is hypothesized that:

H 12: Compatibility positively influences the PU of the m-LMS.

H 13: Compatibility positively influences the PEOU of the m-LMS.

Convenience

Convenience refers to the suitability or ease of performing an action, such as mobile learning, in order to meet a need. Researchers have argued that online learning is more convenient and flexible, as perceived by students, especially in circumstances like the COVID-19 pandemic (Muthuprasad et al., 2021). The convenience of m-LMS is the result of its integrated features, such as time flexibility, information availability, and collaboration tools. Therefore, convenience is a predictor of online learning adoption (Shankar, 2021).

M-learning convenience positively influences the students' PU and PEOU (Cheng, 2015). The perceived convenience of e-textbooks also affects readers' PU and PEOU (Lai & Ulhas, 2012). Similarly, online learning management systems' convenience positively influences the students' PU and PEOU (Mokhtar et al., 2018). Therefore, it is hypothesized that:

H14. Convenience positively influences the PU of the m-LMS.

H15. Convenience positively influences the PEOU of the m-LMS.

Personal Features

Self-efficacy

Self-efficacy (SE) is defined as "domain and task-specific beliefs that people have about their capacity to organize resources and execute courses of action needed to successfully perform tasks" (Hanham et al., 2021, p. 3). SE is a strong predictor of behavior (Spagnolli et al., 2016). SE also influences PU, PEOU, and the adoption of information systems (Abdullah et al., 2016; Al-Adwan, 2020; Al-Adwan et al., 2022; Jin, 2014). Therefore, it is hypothesized that:

H16. Self-efficacy positively influences the PU of the m-LMS.

H17. Self-efficacy positively influences the PEOU of the m-LMS.

Personal innovativeness

Personal innovativeness (PI) is the level of confidence in exploring new information systems. PI is a characteristic that influences IS adoption (Rogers, 2010). Students with higher PI are more likely to adopt mobile learning, despite uncertainty (Liu et al., 2010). The PI of mobile commerce users positively influences PU and PEOU of mobile commerce (Yang, 2005). Kuo and Yen (2009) have confirmed the positive influence of PI on PEOU of mobile services. Han and Shin (2016) have also confirmed the positive influence of PI on m-LMS adoption. Therefore, it is hypothesized that:

H18. Personal innovativeness positively influences the PU of the m-LMS.

H19. Personal innovativeness positively influences the PEOU of the m-LMS.

Enjoyment

Enjoyment is the users' feeling of pleasure when interacting with information systems (Qiu & Benbasat, 2009). In the context of online learning, enjoyment is related to the exciting and pleasant experience of using an online learning platform (Armenteros et al., 2013). Enjoyment is a predictor of IS adoption (Al-Rahmi et al., 2021; Rahmi et al., 2018). Venkatesh and Bala (2008) have proposed that enjoyment is an antecedent of PEOU, an indirect antecedent of PU, and usage intentions.

Prior research has consistently shown that perceived enjoyment positively affects students' PU and PEOU in e-learning systems. A review by Rahmi et al. (2018) of 16 studies found that 13 studies confirmed that perceived enjoyment positively influences PU, and 12 studies confirmed that perceived enjoyment positively influences PEOU. Sun and Zhang (2006) also found that a lack of enjoyment could indicate a feeling of needing more effort to use the system. Therefore, it is hypothesized that:

H20. Enjoyment positively influences the PU of the m-LMS.

H21. Enjoyment positively influences the PEOU of the m-LMS.

Social Factor

The need for m-LMS has increased during the time of COVID-19. Therefore, the positive influence of other users exerts a strong impact on the m-LMS usage continuance intentions. Therefore, social influence factors are investigated in the current study.

Social influence

The concept of social influence refers to individuals' inclination to conform to the opinions and attitudes of others in order to maintain positive relationships within a group (Hernandez et al., 2011). Previous studies have established that individuals may adopt information systems solely because of the influence of others. Research by Ifinedo (2016) has shown that social recognition positively influences students' adoption of social networking sites. Social influence also plays a role in shaping individuals' intent to adopt IS (Al-Nawayseh et al., 2019; Venkatesh et al., 2003).

Wu and Chen (2017) define social influence as the positive reinforcement and support that individuals receive from others when they take part in online learning. Students can have an impact on one another in m-LMS environments (Al-Adwan et al., 2018a, 2018b). This usage is likely to be seen as more beneficial and convenient when other students view it in this way. Social influence positively influences PU of an e-learning system and individuals' attitudes toward using the e-learning system. Therefore, it is hypothesized that:

H22. Social influence positively influences the PU of the m-LMS.

H23. Social influence positively influences the PEOU of the m-LMS.

RESEARCH METHODOLOGY

This study utilized a quantitative approach to develop and evaluate a comprehensive model that predicts students' engagement with and intent to continue using mobile-Learning Management Systems (m-LMS). Participants with prior experience with m-LMS were recruited for the study. The proposed model draws on the Technology Acceptance Model (TAM), Task-Technology fit (TTF), and other related models to identify factors that affect student engagement and continuance intention. Partial Least Squares-Structural Equation Modeling (PLS-SEM) was used to evaluate the model.

PLS-SEM is a multivariate analysis technique that allows for the evaluation of complex models with latent variables. This approach was chosen due to its ability to handle non-normal data, model complex relationships between variables, and provide reliable estimates even with small sample sizes. The use of PLS-SEM allowed for the evaluation of the proposed model's predictive capability and the identification of significant factors affecting student engagement and continuance intention.

By using a quantitative approach and PLS-SEM methodology, this study provides a comprehensive model that takes into account a variety of factors affecting engagement and continuance intention and has a strong predictive capability. The methodology used in this study allows for the rigorous evaluation of the proposed model and provides important insights into the factors that influence student engagement and continuance intention with m-LMS.

INSTRUMENTS AND SURVEY DEVELOPMENT

The measurement items for this study were adopted from previous research and have been utilized and validated in multiple studies. They were rephrased to be applicable to the m-LMS context. The final survey consists of three sections: the first section explains the purpose and background of the study, the second section includes demographic questions, and the last section includes the 33 chosen measurement items.

The survey items were reviewed for face validity by three information systems professors, and some items were modified as needed. To test the reliability and validity of the instruments, a pilot study was conducted on a group of 25 Information Technology students. The results of the pilot study revealed that all factor loadings and Cronbach's alpha values were above 0.7, meaning that the survey instruments have good reliability. Overall, the pilot study results showed that the survey instruments have good reliability and can be used to measure the intended construct. A 7-point Likert scale was employed for the items' measurement, where 1 represents 'totally disagree' and 7 represents 'totally agree'. The final measurement items are included in the Appendix.

DATA COLLECTION

To ensure that participants had a sufficient level of familiarity and knowledge of the subject matter, we selected university students who had experience using mobile-Learning Management Systems (m-LMS) in their courses. Specifically, we recruited 800 students who had been enrolled in courses taught by five professors at a public university in Jordan, all of whom had implemented m-LMS in their courses. A convenience sampling method was used for recruitment as it allowed us to access participants who met the inclusion criteria easily. The professors agreed to send an email invitation to their students on our behalf, and interested students who met the criteria were invited to participate in the study.

A total of 253 students returned valid survey responses, resulting in a response rate of 31.63%. This sample size was deemed sufficient according to the recommendations of Stevens (2012), which state that a minimum of 15 respondents per predictor is required. In this case, a minimum of 210 respondents were needed, and a sample of 253 met this requirement. The data was collected between January and March 2022. The demographic characteristics of the respondents are shown in Table 1.

Table 1. Demographics characteristics of the respondents

Items	Type	Frequency (n = 253)	Percent (%)
Gender	Male	111	43.9%
	Female	142	56.1%
Age (years)	Less than 20	44	17.4%
	20- Less than 23	161	63.7%
	23- Less than 26	32	12.6%
	26 or more	16	6.3%
Academic year	First year	48	19%
	Second year	140	55.3%
	Third year	37	14.6%
	Fourth year	28	11.1%
Time to participate in m-LMS per week (hours)	Under 5	97	38.3%
	5-10	105	41.5%
	10 or more	51	20.2%

DATA ANALYSIS AND RESULTS

Partial Least Square-Structural Equation Modeling (PLS-SEM) was employed to evaluate the proposed research model. PLS-SEM was chosen because the study's objective is to predict the constructs of engagement and continuance intention. Other models, such as CB-SEM, are more suitable for studies that focus on theory confirmation (Goodhue et al., 2012). WarpPLS 7.0 was utilized to conduct the statistical assessment.

MEASUREMENT MODEL ASSESSMENT

In the analysis of the measurement model, the reliability of the data was assessed by examining the consistency of individual items and the overall consistency of the constructs being measured (Wong, 2013). The reliability of individual items was determined by analyzing the strength of their loadings on their corresponding constructs, with a minimum acceptable loading of 0.707 (Koufteros, 1999). As presented in the Appendix, the results indicate that all individual items had loadings of at least 0.707 on their respective constructs. For the composite reliability, Cronbach's alpha coefficient of each construct was also evaluated, with a minimum threshold of 0.7. As presented in Table 2, the results indicate that Cronbach's alpha coefficients for all constructs exceeded the minimum threshold of 0.7.

The validity of the study was established through the examination of convergent and discriminant validity. Convergent validity was assessed by calculating the average variance extracted (AVE) for each construct and ensuring that it met the threshold of 0.5 as per Hair et al. (2012). Table 2 shows that all AVE values met this criterion. Discriminant validity was established by comparing the AVE to the squared correlation between constructs, as per Hair et al. (2012). Table 2 demonstrates that all constructs met these criteria.

Table 2. Discriminant validity analysis

			Square Root of AVE and inter-construct correlations													
Cron-bach's Alpha	**AVE**	**Constructs**	**TTF**	**COM**	**CON**	**SE**	**PI**	**ENJ**	**SI**	**PU**	**PEU**	**PAC**	**PS**	**P2C**	**ENJ**	**CI**
.775	.743	**TTF**	**.862**													
.824	.714	**COM**	.521	**.845**												
.79	.724	**CON**	.352	.332	**.851**											
.763	.659	**SE**	.459	.303	.418	**.812**										
.710	.615	**PI**	.358	.312	.402	.453	**.784**									
.713	.482	**ENJ**	.348	.444	.307	.338	.493	**.694**								
.777	.507	**SI**	.367	.302	.322	.336	.373	.354	**.712**							
.725	.716	**PU**	.357	.352	.376	.479	.431	.356	.483	**.846**						
.805	.674	**PEU**	.325	.329	.423	.354	.359	.393	.354	.463	**.821**					
.856	.682	**PAC**	.451	.38	.429	.411	.333	.329	.348	.383	.357	**.826**				
.737	.584	**PS**	.368	.462	.41	.459	.446	.496	.414	.466	.344	.384	**.764**			
.765	.551	**P2C**	.342	.305	.402	.402	.446	.312	.314	.402	.324	.387	.457	**.742**		
.775	.746	**ENG**	.324	.486	.376	.459	.358	.368	.38	.491	.476	.469	.373	.475	**.864**	
.824	.661	**CI**	.359	.44	.383	.414	.417	.333	.302	.315	.469	.482	.409	.427	.361	**.813**

STRUCTURAL MODEL ASSESSMENT

The study by Hair et al. (2016) examined the structural model for collinearity issues by assessing Tolerance and Variance Inflation Factors (VIFs). To ensure that there is no multicollinearity, tolerance values should be above 0.2, and VIF values should be below 5. The study's results indicate that these conditions are met.

R^2 values and the path coefficients are displayed in Figure 3. The R^2 value for PU was 0.827, the R^2 value for PEOU was 0.531, the R^2 value for continuance intention was 0.835, and the R^2 value for engagement was 0.528. Therefore, the predictive power of PEOU and engagement is moderate, according to the recommendations of Mokhtar et al. (2018), which suggest an R^2 value of at least 50%. Meanwhile, the predictive power of PU and continuance intention is substantial.

For hypothesis testing, the current study considered path coefficients (see Table 3). The results indicate that mobile learning management system factors (Task-Technology Fit [β=.226, $p<0.001$], Compatibility [β=.202, $p<0.001$], and Convenience [β=.196, $p<0.001$]) have significant impacts on perceived usefulness, supporting Hypotheses 10, 12, and 14. Personal factors (Self-Efficacy [β=.191, $p<.001$], Personal Innovativeness [β=.111, $p<.01$], and Enjoyment [β=0.194, $p<0.001$]) also have significant impacts on perceived usefulness, supporting Hypotheses 16, 18, and 20. Furthermore, the social factor (Social Influence [β=0.081, $p<0.05$]) has a significant impact on perceived usefulness, supporting Hypothesis 22.

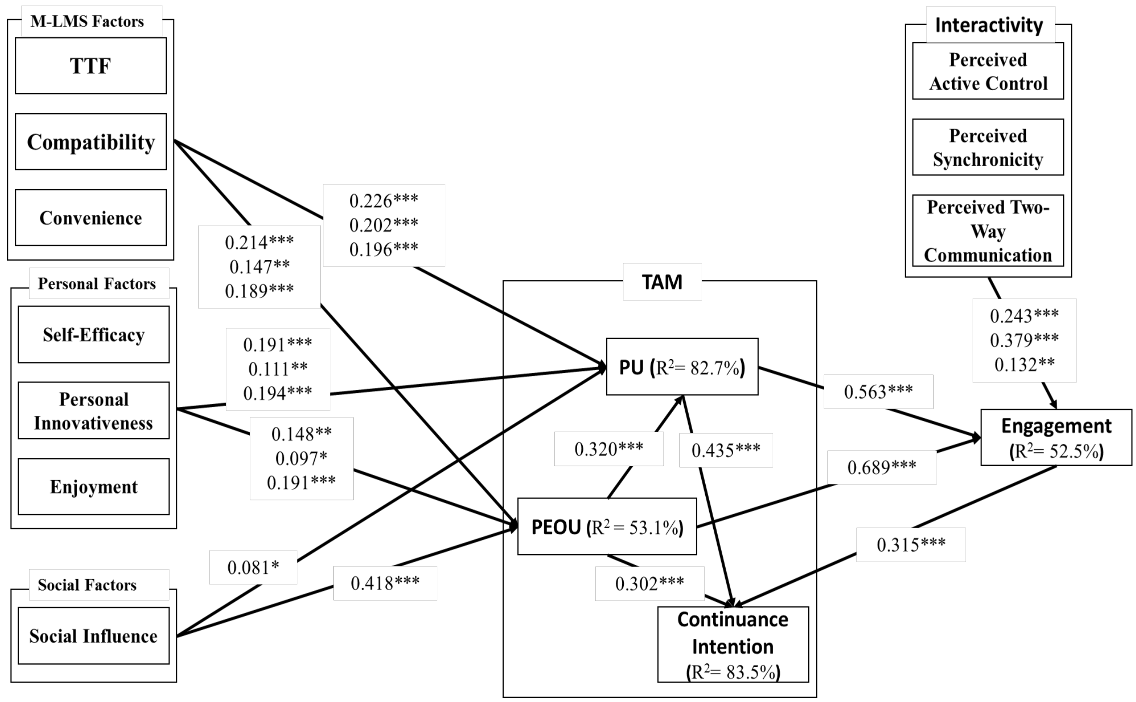

Figure 3. Path analysis

Similarly, m-LMS factors (Task-Technology Fit [β=.214, p<0.001], Compatibility [β=.147, p<0.01], and Convenience [β=.189, p<0.001]) have significant impacts on perceived ease of use, supporting Hypotheses 11, 13, and 15. Personal factors (Self-Efficacy [β=.148, p<0.01], Personal Innovativeness [β=.097, p<0.05], and Enjoyment [β=0.191, p<0.001]) also have significant impacts on perceived ease of use, supporting Hypotheses 17, 19, and 21. Additionally, the social factor (Social Influence [β=0.418, p<0.001]) has a significant impact on perceived ease of use, supporting Hypothesis 23.

Interactivity factors (Perceived Active Control [β=0.243, p<0.001], Perceived Synchronicity [β=.379, p<0.001], and Perceived Two-Way Communication [β=.132, p<0.01]) have significant impacts on engagement, supporting Hypotheses 7, 8, and 9. PU [β=0.563, p<.001], and PEOU [β=0.689, p<0.001] have significant impacts on engagement, supporting Hypotheses 4 and 5. PEOU [β=0.320, p<0.001] has a significant impact on PU, supporting Hypothesis 6. Finally, engagement [β=0.315, p<0.001], PU [β=0.435, p<.001], and PEOU [β=0.302, p<.001] have significant impacts on continuance intention, supporting Hypotheses 1, 2, and 3.

DISCUSSION

This study aims to investigate students' engagement with m-LMS and their intentions to continue using them. The proposed model incorporates factors related to technology, student characteristics, and social influence.

The findings (Table 3) indicate that m-LMS interactivity factors positively influence student engagement, supporting the importance of technology-related factors in engaging students. Additionally, students' perceived PU and PEOU of m-LMS have positive impacts on engagement, which aligns with previous research by McLean (2018). Furthermore, engagement positively influences the students' continuance intentions to use m-LMS, as confirmed in prior research by Shiau and Luo (2013), and Shao and Chen (2020). Additionally, students' PU and PEOU influence their continuance intentions, consistent with the TAM theory, and consistent with research by Brahmasrene and Lee (2012).

The study findings indicate that the factors related to m-LMS positively influence the students' PU and PEOU of m-LMS. Specifically, when students find that m-LMS align with their learning needs, are compatible with their learning style, and are convenient for their learning activities, they are more likely to view m-LMS as a valuable and user-friendly tool. Additionally, the study's findings regarding technology acceptance factors, such as TTF, compatibility, and convenience, align with previous research in the field (Cheng, 2015; Purnomo & Lee, 2013; Wu & Chen, 2017). Furthermore, students' personal factors such as their self-efficacy also positively influence their PU and PEOU of m-LMS.

Self-efficacy and personal innovativeness positively influence the students' PEOU and PU of m-LMS. Specifically, students who have an inclination towards innovation and experimentation will view m-LMS as valuable and easy to use. These findings align with previous research, including studies by Jin (2014) and Yang (2005). Additionally, the study also found that enjoyment positively influences PU and PEOU, which is consistent with prior research by Rahmi et al. (2018). Social influence also positively influences PU and PEOU. Students influence each other's perceptions of m-LMS usefulness and ease of use, consistent with findings from Wu and Chen (2017), and Mo et al. (2021).

Table 3. The study's results

Hypotheses #	Path	Path Coefficient	P Values	Support
H1	Engagement ➔ Cont. Intention	0.315	p < 0.001***	Yes
H2	PU ➔ Cont. Intention	0.435	p < 0.001***	Yes
H3	PEOU ➔ Cont. Intention	0.302	p < 0.001***	Yes
H4	PU ➔ Engagement	0.563	p < 0.001***	Yes
H5	PEOU ➔ Engagement	0.689	p < 0.001***	Yes
H6	PEOU ➔ PU	0.320	p < 0.001***	Yes
H7	PAC ➔ Engagement	0.243	p < 0.001***	Yes
H8	PS ➔ Engagement	0.379	p < 0.001***	Yes
H9	P2C ➔ Engagement	0.132	p < 0.01**	Yes
H10	TTF ➔ PU	0.226	p < 0.001***	Yes
H11	TTF ➔ PEOU	0.214	p < 0.001***	Yes
H12	Compatibility ➔ PU	0.202	p < 0.001***	Yes
H13	Compatibility ➔ PEOU	0.147	p < 0.01**	Yes
H14	Convenience ➔ PU	0.196	p < 0.001***	Yes
H15	Convenience ➔ PEOU	0.189	p < 0.001***	Yes
H16	Self-Efficacy ➔ PU	0.191	p < 0.001***	Yes
H17	Self-Efficacy ➔ PEOU	0.148	p < 0.01**	Yes
H18	Personal Innovativeness ➔ PU	0.111	p < 0.01**	Yes
H19	Personal Innovativeness ➔ PEOU	0.097	p < 0.05*	Yes
H20	Enjoyment ➔ PU	0.194	p < 0.001***	Yes
H21	Enjoyment ➔ PEOU	0.191	p < 0.001***	Yes
H22	Social Influence ➔ PU	0.081	p < 0.05*	Yes
H23	Social Influence ➔ PEOU	0.418	p < 0.001***	Yes

Implications for Theory and Practice

The study's results contribute to the understanding of the factors that affect students' engagement and usage continuance intentions with m-LMS and provide valuable insights for both theory and practice.

The study provides implications for theory. The study's findings provide evidence for the positive influence of students' perceived usefulness (PU) and perceived ease of use (PEOU) on their engagement in mobile-Learning Management Systems (m-LMS) and their usage continuance intentions. The findings also support the influence of the proposed factors (m-LMS factors, personal factors, and social factors) on PU and PEOU of m-LMS. The study's attempt to build an integrated model that combines factors from the Technology Acceptance Model (TAM), the Task-Technology Fit (TTF) model, and a model proposed by Mokhtar et al. (2018) contributes to the understanding of the antecedents of student engagement in m-learning technologies.

The study also provides implications for practice. Decision makers and m-LMS designers can use the study's results to engage students in m-learning tools and increase their knowledge about the factors that affect students' engagement and usage continuance intentions. Higher education institutions can use the results to support students' personal traits, such as self-efficacy, personal innovativeness, and enjoyment, to enhance their engagement in the university's m-LMS. Designers of m-learning technologies can use the study's findings on the antecedents of engagement to design engaging applications that students will continue to use in the future.

Limitations and Future Recommendations

The study's findings enhance the current research on students' engagement in m-LMS, yet the study has some limitations that represent an opportunity for future research. The current study provides a group of antecedents that influence students' engagement in m-LMS. However, there could be other factors that can be added to the model and make it more predictive of the students' engagement in m-LMS, and their intention to continue using m-LMS in the future. For instance, subjective norms can be explored by further studies.

Adding moderating factors, like age, gender, and prior experience with m-LMS, might strengthen the model. Finally, relying on a convenient sample from one public university in Jordan could be another limitation of the study. Future studies can replicate the study by using a more representative sample.

Conclusion

The aim of the current study was to develop a model that predicts students' engagement with and intent to continue using Mobile-Learning Management Systems (m-LMS). The study used a combination of the Technology Acceptance Model (TAM), the Task-Technology Fit (TTF), and other related models to formulate the proposed model. The sample size consisted of 253 students who had prior experience with m-LMS, and the proposed model was evaluated using Partial Least Squares-Structural Equation Modeling (PLS-SEM).

The study's findings support previous research and provide evidence for the strong predictive capability of the proposed model. The results of the study can inform researchers about which factors within the technology acceptance model have the strongest correlation to engagement, allowing them to make more informed decisions about how to improve m-LMS platforms. Educational institutions should consider these results in order to effectively meet the needs of students for interactive, effective, and user-friendly m-LMS platforms.

The proposed model can help educational institutions to understand how to improve student engagement and continuance intention with m-LMS, ultimately leading to more effective and efficient mobile learning. Additional research should be conducted to test the proposed model in different contexts and with different populations to further validate its applicability.

In summary, the current study provides a comprehensive model that takes into account a variety of factors affecting engagement and continuance intention, and it has a strong predictive capability. The study provides valuable insights for researchers in the field of mobile-learning management systems (m-LMS) by highlighting the importance of understanding the antecedents of students' engagement. The results of the study have the potential to improve m-LMS platforms and ultimately lead to more effective and efficient mobile learning for students.

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APPENDIX: QUESTIONNAIRE ITEMS

Construct	Items		Item Loading	Reference
Engagement	ENG1	The m-LMS kept me totally absorbed in the browsing.	.791	Webster & Ahuja (2006)
	ENG2	The m-LMS held my attention.	.815	
	ENG3	The m-LMS excited my curiosity.	.845	
	ENG4	The m-LMS aroused my imagination.	.804	
	ENG5	The m-LMS was fun.	.788	
	ENG6	The m-LMS was intrinsically interesting.	.812	
	ENG7	The m-LMS was engaging.	.794	
PU	PU1	M-LMS enhances my course performance	.875	Mokhtar et al. (2018), Coşkunçay (2013)
	PU2	M-LMS increases productivity of the course	.847	
	PU3	M-LMS helps me to satisfy the purpose of the course easily	.862	
	PU4	M-LMS gives me a greater control over my course	.852	
PEOU	PEOU1	Interacting with m-LMS is clear and understandable	.847	Mokhtar et al. (2018), Coşkunçay (2013)
	PEOU2	Interface of the m-LMS is clear and easy to understand	.894	
	PEOU3	Navigation among tools is not difficult	.834	
	PEOU4	Interacting with m-LMS is not complicated	.811	
Continuance Intention	CI1	I intend to continue using the m-LMS rather than use any alternative technology.	.879	Limayem et al. (2007)
	CI2	My intentions are to continue using the m-LMS rather than use any alternative technology.	.786	
	CI3	If I could, I would like to continue my use of the m-LMS.	.714	
Perceived Active Control	PCA1	I have a great deal of control over my using experience in the m-LMS.	.713	Shao & Chen (2020), Liu (2003)
	PCA2	The m-LMS is manageable	.735	
	PCA3	While I was using m-LMS, I could choose freely what I wanted to do	.716	
Perceived Synchronicity	PS1	Getting course information through the m-LMS is fast	.758	Shao & Chen (2020), Liu (2003)
	PS2	I can get the instantaneous and newest course information from the m-LMS	.748	
	PS3	I can get fast responses to my request through the m-LMS	.768	
Perceived Two-Way Communication	P2WC1	The m-LMS facilitates concurrent communication between learners and instructors, and among learners	.784	Shao & Chen (2020), Liu (2003)
	P2WC2	The m-LMS gives me the opportunity to talk back with instructors or other learners	.739	
	P2WC3	The m-LMS enables conversation between learners and instructors, and among learners	.741	

Construct	Items		Item Loading	Reference
TTF	TTF1	The functions of m-LMS are enough to help manage my academic work.	.792	Mokhtar et al. (2018)
	TTF2	The functions of m-LMS are appropriate to help manage my academic work.	.775	
	TTF3	In general, the functions of m-LMS fully meet my needs of academic work.	.769	
Compatibility	COM1	Using the m-LMS is compatible with all aspects of my academic activities.	.842	Venkatesh et al. (2003)
	COM2	I think that using the m-LMS fits well with the way I like to do my academic activities.	.791	
	COM3	Using the m-LMS fits into my study style.	.784	
Convenience	CON1	Using m-LMS enables me to search for the academic information/content I need without time constraints when learning.	.748	Lai & Ulhas (2012)
	CON2	Using m-LMS saves my effort in learning.	.804	
	CON3	Using m-LMS enables me to download academic information/content when learning.	.819	
	CON4	Using m-LMS enables me to learn quickly	.879	
Self-Efficacy	SE1	I can use m-LMS without support	.842	Coskuncay (2013)
	SE2	I can use m-LMS, even if there is no one for help when I get stuck	.801	
	SE3	I was able to use m-LMS without observing anyone use it	.746	
Personal Innovativeness	PIN1	If I heard about a new information technology, I would look for ways to experiment with it.	.909	Xu et al. (2009)
	PIN2	Among my peers, I am usually the first to try out new information technologies.	.887	
	PIN3	I like to experiment with new information technologies.	.869	
Enjoyment	ENJ1	I find my experience with m-LMS interesting.	.847	Jiang & Benbasat (2007)
	ENJ2	I find my experience with m-LMS enjoyable.	.825	
	ENJ3	I find my experience with m-LMS exciting.	.815	
	ENJ4	I find my experience with m-LMS fun.	.861	
Social Influence	SIN1	Other leaners' beliefs about m-LMS encourage me to use it.	.867	Hernandez et al., (2011)
	SIN2	Other leaners' beliefs about m-LMS influence my degree of m-LMS usage.	.815	
	SIN3	Other leaners' beliefs about m-LMS condition me to use it.	.894	

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