Understanding mobile learning continuance from an online-cum-offline learning perspective: a SEM-neural network method

Miao Zhang

School of Education Science and Technology,
Zhejiang University of Technology,
Hangzhou, 310014, China
Email: miranda.zhangm@foxmail.com

Yuangao Chen, Shuai Zhang, Wenyu Zhang, Yixiao Li and Shuiqing Yang*

School of Information Management and Artificial Intelligence,
Zhejiang University of Finance and Economics,
No. 18, XueYuan Street, XiaSha Higher Education Zone,
Hangzhou City 310018, China
Email: chenyg@zufe.edu.cn
Email: zs760914@sina.com
Email: wyzhang@e.ntu.edu.sg
Email: yxli@zufe.edu.cn
Email: yangshuiqing@zufe.edu.cn
*Corresponding author.

Abstract: Based on uses, gratifications theory and literature related to perceived integration, this study investigated the factors that influence college students' mobile learning continuance from an online-cum-offline learning perspective. A research model was developed and tested against data collected from 261 college students who are the mobile learning users of an online flipped learning platform in China. A multi-analytic method was employed whereby the proposed model was first tested using structural equation modelling (SEM), and the results of the SEM were used as inputs for a neural network approach to explain mobile learning continuance. The results show that perceived integration affects mobile learning continuance directly and indirectly via students' extrinsic gratification (social need) and intrinsic gratifications (affective need and entertainment need). According to the normalised importance, affective need is the most significant factor affecting mobile learning continuance, following by social need and entertainment need.

Keywords: mobile learning; perceived integration; gratifications; neural network; multi-analytic method.

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Biographical notes: Miao Zhang is currently a Master's candidate in the School of Education Science and Technology at the Zhejiang University of Technology, China. Her research interests include mobile learning and smart service adoption.

Yuangao Chen is a Professor at the School of Information Management and Artificial Intelligence at the Zhejiang University of Finance and Economics, China. His current research focuses on online customer behaviour, e-supply chain management, and service operations management. His research works have been published in *Information Science*, *Information Technology and Management*, *International Journal of Networking and Virtual Organizations*, *Electronic Commerce Research*, and several other refereed journals.

Shuai Zhang is a Professor at the School of Information Management and Artificial Intelligence at Zhejiang University of Finance and Economics, China. He has published more than 30 papers in international journals in the recent ten years, including bibliometrics, supply chain management, business intelligence, data mining, e-government, and manufacturing informatisation.

Wenyu Zhang received his BS from the Zhejiang University, China, in 1989, and PhD from the Nanyang Technological University, Singapore, in 2002. He is currently a Full-Time Professor with the School of Information Management and Artificial Intelligence, Zhejiang University of Finance and Economics, Hangzhou, China. He has published more than 40 papers in international journals and more than 20 papers in international conference proceedings in the recent ten years, including supply chain management, digital library, bibliometrics, concurrent engineering, distributed manufacturing, business intelligence, business analytics, data mining, multi-agent technology, and semantic web.

Yixiao Li is currently a Professor in the School of Information Management and Artificial Intelligence at the Zhejiang University of Finance and Economics, China. He received his PhD in Computer Science from the Zhejiang University, China, respectively. His research interests include mobile learning, emergency management, and social networks. He has published over 20 papers in referred conference proceedings and journals.

Shuiqing Yang is currently an Associate Professor in the School of Information Management and Artificial Intelligence at the Zhejiang University of Finance and Economics, China. His research interests include technology implementation, innovation adoption and diffusion, mobile learning adoption, and related topics. He has published over 30 papers in referred journals such as *Decision Support Systems*, *Information and Management*, *International Journal of Mobile Communications*, *International Journal of Human-Computer Interaction*, among others.

1 Introduction

The advancement of mobile technologies and the proliferation of mobile devices have facilitated the rapid growth of mobile learning (m-learning) usage (Chung et al., 2019; Nie et al., 2020). M-learning is defined as the delivery of learning activities through the use of mobile devices and wireless internet, which enable students to learn anytime and anywhere (Hamidi and Chavoshi, 2018; Hashim et al., 2015). The m-learning mode creates a flexible learning pedagogy that offers educators with the opportunity to redefine teaching and learning (Heflin et al., 2017; Joo et al., 2016). For instance, m-learning enables educators to provide students with educational contents based on their needs by adopting a push-based strategy (Motiwalla, 2007). Indeed, by providing ubiquitous, convenient, and personalised learning services, m-learning has dramatically changed the way students learn and interact between online and offline learning (Yang et al., 2019; Zydney and Warner, 2016). For example, students can prepare for their classes by engaging with online educational materials including educational videos and online quizzes through a m-learning platform, even when they travel by bus or other means of transportation. On the other hands, when students are attending an on-campus face-to-face lecture, they can also instantly interact with their classmates and teachers on the lecture's online forum through the m-learning platform. Previous studies has also suggested that m-learning will never replace traditional classroom or other e-learning modes (Motiwalla, 2007; Wang et al., 2009). In related stead, m-learning builds a 'bridge' between face-to-face classroom and web-based virtual learning pedagogy, effectively integrating students' online and offline learning activities. Therefore, it is important to explore the factors that affect m-learning usage behaviours from the perspective of online-cum-offline learning.

In academia, despite a great deal of prior efforts devoted to understanding m-learning adoption and usage behaviours (Hashim et al., 2015; Heflin et al., 2017; Nie et al., 2020), most of the studies have regarded students' online and offline learning as isolated from one another, and identified antecedents of m-learning usage behaviours in a single-channel environment. Scholars have seldom investigated the important role of the mobile-based online and offline learning integration in shaping students' m-learning behaviours. In addition, the extant studies tend to utilise the leading information technology (IT) theories, such as technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT), to explain m-learning adoption and usage behaviours (Hamidi and Chavoshi, 2018; Karimi, 2016; Park et al., 2012). Despite TAM and its expanded models have been validated as the very useful frameworks in predicting technology usage, they are unable to explain 'how and why' people use certain media to satisfy needs due to the black box features (Guo et al., 2010). A review of existing literature suggests that the uses and gratifications (U&G) theory (Katz et al., 1973), which reflects the underlying users' motivations, might offer an explanation as to how and why learners are motivated to continue use of m-learning.

It is noted that higher education students will be more likely to embrace and use m-learning than K-12 students, as they usually have their own mobile devices (Cheon et al., 2012). However, the situations of m-learning diffusion in higher education nowadays are far from what many scholars and educators expect (Kim et al., 2017). Despite plenty of universities offer free m-learning applications, still many students discontinued its usage soon after their initial adoption. Indeed, m-learning can only be meaningful when the learner is self-motivated and actively participates in and engages in the learning process, not just adopting m-learning applications in an initial usage stage (Joo et al., 2016). M-learning continuance reflects the degree of a learner's intention to continue use of m-learning, which is an important indicator of the success of m-learning diffusion. If m-learning developers or educators cannot retain the initial users and facilitate their long-term use, they will still not be able to win the battle of m-learning diffusion (Huang and Chiu, 2015; Nie et al., 2020; Yang et al., 2019). Therefore, to ensure the success of m-learning in higher education, it is critical for us to understand what factors motivate college students to continue use of m-learning, especially from the perspective of online-cum-offline learning.

Furthermore, unlike previous studies that adopted linear models [such as structural equation modelling (SEM)] to explain user behaviours, the present study employs a SEM-neural network combined approach to explain and predict the determinants of m-learning continuance. SEM is primarily used for theoretical testing and linear relationships modelling, and can sometimes oversimplify the complexities of students' decision to use m-learning (Sharma et al., 2017). This disadvantage of SEM can be overcome by neural network modelling. On the other hand, neural network modelling has the ability to detect complex linear and nonlinear relationships among variables, but is not suitable for theoretical validating due to its 'black box' nature (Hew et al., 2016; Sharma et al., 2017). The SEM-neural network approach thus can take the advantages of both the SEM and neural network approaches (Hew et al., 2016; Liébana-Cabanillas et al., 2017; Sharma et al., 2017). In our study, SEM will be first applied to verify the causal relationships in the proposed model, and then the supported relationships in the SEM will be used as inputs to the neural network model to predict m-learning continuance (Liébana-Cabanillas et al., 2017; Sharma et al., 2017).

Based on U&G theory and studies related to perceived integration, the present study examines the factors that affect college students' m-learning continuance by employing a SEM-neural network approach. Specifically, our study investigates

1 How do college students' extrinsic gratifications (cognitive need and social need) and intrinsic gratifications (affective need and entertainment need) influence their m-learning continuance intention?

2 What is the role of perceived integration on college students' intention to continue using m-learning?

The present study thus provides not only a theoretical understanding of m-learning continuance, but also offers practical insights to m-learning developers or educators for managing such continuance use.

The remainder of this study is structured as follows. Section 2 presents a literature review regarding m-learning studies. Then, the theoretical foundation and research hypotheses are presented in Section 3, followed by the description of research methodology and data collection in Section 4. The results of data analysis are presented in Section 5, followed by the discussion of the results in Section 6. Finally, the present study concludes by summarising the findings, the theoretical and practical implications as well as limitations.

2 Literature review

M-learning has received increasingly attentions from scholars and educators in recent years (Chung et al., 2019; Nie et al., 2020). For instance, drawing on the theory of planned behaviour, Nie et al. (2020) examined the factors that affect mobile English learning check-in behaviour. Still, several literature review-based studies provided important insights for understanding m-learning research and practice (Chee et al., 2017; Hwang and Wu, 2014; Pimmer et al., 2016; Wu et al., 2012). For instance, based on a meta-analysis of 164 refereed journal articles published from 2003 to 2010 in major journals, Wu et al. (2012) found that most studies of m-learning focus on effectiveness evaluation, following by m-learning system design. Hwang and Wu (2014) conducted a review on the 2008–2012 publications in seven major educational technology-enhanced learning journals. In line with Wu et al. (2012), they found that most studies focus on m-learning effectiveness. Similarly, Chee et al. (2017) adopted text mining techniques to analysis of 144 refereed journal articles published from 2010 to 2015 in top six major educational technology-based learning journals. They also found that evaluating effectiveness of m-learning is the current scholars' most common research propose. Pimmer et al. (2016) reviewed 36 empirical m-learning related papers in higher education contexts. They emphasised that the empirical studies on m-learning in higher education environment are still limited.

Thanks to these efforts, we have a better understanding about the status of m-learning study and practice. However, despite advances in existing studies, a review of the extant literature shows that most studies tended to focus on technology-related enablers to explain initial adoption and post-usage of m-learning (Karimi, 2016; Park et al., 2012; Wang et al., 2009). Factors such as performance expectancy, perceived usefulness of mobile technology, and effort expectancy are identified to affect adoption and usage of m-learning (Park et al., 2012; Sarrab et al., 2016). However, the underlying mechanisms of the learners' motivations on m-learning usage have been rarely explored (Hashim et al., 2015; Kim et al., 2017).

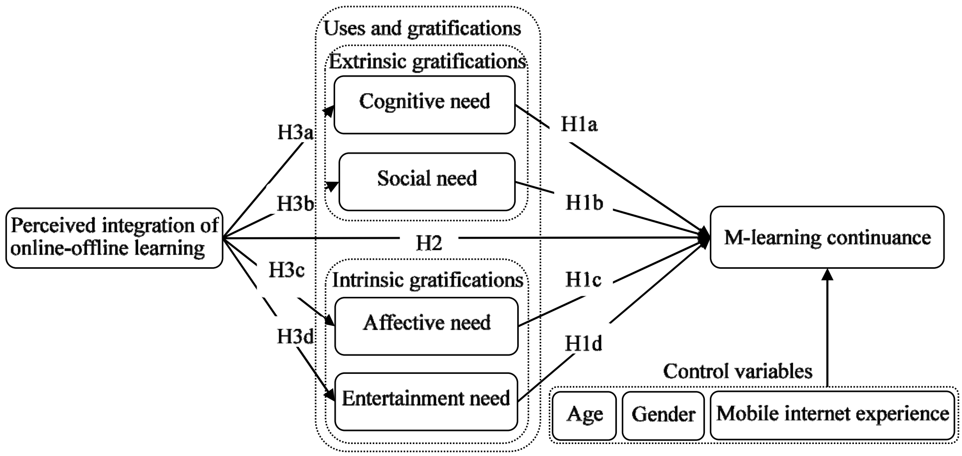
As a framework for explaining individuals' motives for media usage, the U&G theory provides an explanation of how and why students are motivated to continue use of m-learning (Hashim et al., 2015; Mondi et al., 2008; Punyanunt-Carter et al., 2017). According to the U&G theory, people gain gratifications through the media, which satisfy their various needs including cognitive, social, affective, and entertainment needs (Hashim et al., 2015; Mondi et al., 2008). Different from the TAM and its expanded models that explain workplace technology use, the U&G theory explains how and why users actively select specific new media from a motivational perceptive (Katz et al., 1973). The U&G theory thus fits well into the motivational perceptive for explaining college students' m-learning continuance behaviours in the present study.

In addition, as the boundaries between students' online and offline learning are increasingly blurred by using m-learning platform, investigating students' m-learning continuance behaviours requires the researchers to look beyond the perspective of single-channel learning. Therefore, this study intends to investigate the impacts of learning gratifications on students' m-learning continuance behaviours by considering the effects of perceived integration from the online-cum-offline learning perspective.

3 Theoretical foundation and research hypotheses

Drawing on the U&G theory and literature related to perceived integration (Delgado-Ballester and Hernández-Espallardo, 2008; Hashim et al., 2015; Punyanunt-Carter et al., 2017; Yang et al., 2016a), the present study develops a research model that reflects the impacts of perceived integration and learning gratifications on students' intention to continue use of m-learning in higher education context (Figure 1). It depicts that perceived integration will positively affect extrinsic gratifications (cognitive need and social need) and intrinsic gratifications (affective need and entertainment need) which further affect continuance intention of using m-learning. Theoretical justifications of the proposed hypotheses are discussed in Figure 1.

Figure 1 Research model



3.1 U&G theory

Derived from mass communication literature, the U&G theory offers a user-centred view for explaining individual motivation and behaviour when using specific media (Chen, 2014; Hashim et al., 2015; Wu et al., 2010). A key assumption of the U&G theory is that people are goal-directed in their selection of media outlets and actively integrate media messages within their daily lives, so as to achieve a variety of gratifications (Phua et al., 2017). In other words, people's media consumption is intentional, and they are motivated by a variety of needs and actively seek to fulfil the needs from using the specific media (Gallego et al., 2016).

The U&G theory has been widely adopted to examine media usage in a wide range of contexts including social networks (Phua et al., 2017), online game (Wu et al., 2010), internet news browsing (Zhang and Zhang, 2013), and web-based learning (Chen, 2014; Hashim et al., 2015). However, due to the sophisticated structure and context-dependent nature of use gratifications, extant literature still lacks a consistent viewpoint regarding its dimensions (Mondi et al., 2008; Wu et al., 2010). For instance, Katz et al. (1973) develop the U&G theory and identified eight dimensions of gratifications, including passing time, companionship, escape, enjoyment, social interaction, relaxation, information, and excitement. Cheung et al. (2011) measured the gratifications of social media usage as five dimensions, including purposive value, self-discovery, social enhancement, entertainment value, and interpersonal connectivity maintain. Gallego et al. (2016) identified six dimensions of gratifications including convenience, entertainment, socialising, status seeking, information seeking, sharing experience, and examined their impacts on continuance usage of second life. More recently, Punyanunt-Carter et al. (2017) conceptualised the gratifications of Snapchat usage into two dimensions: entertainment and functional motivations.

In an e-learning context, Mondi et al. (2008) measured the gratifications of m-learning usage by including five dimensions: cognitive, affective, personal integrative, social integrative, and entertainment need. Hashim et al. (2015) conceptualised the adult learners' gratifications into three dimensions: cognitive need, social need, and affective need. A review of the U&G literature reveals that cognitive, social, affective, and entertainment needs are the most frequently used components of gratifications in education settings (Hashim et al., 2015; Mondi et al., 2008). According to the motivation theory (Davis et al., 1992), individuals' motivations have two main aspects: extrinsic motivations and intrinsic motivations. Extrinsic motivations are defined as "where a product or consumption experience serves instrumentally or functionally as a means to some further end" [Holbrook, (2006), p.715], while intrinsic motivations reflected "where a consumption experience is appreciated for its own sake as a self-justifying end-in-itself" [Holbrook, (2006), p.715]. Therefore, based on the U&G theory and extant motivation theory-based studies (Davis et al., 1992; Holbrook, 2006; Yang et al., 2018), the present study categorised the gratifications of m-learning usage into extrinsic and intrinsic gratifications in which

1 cognitive need
2 social need reflected extrinsic gratifications
3 affective need
4 entertainment need captured intrinsic gratifications.

3.1.1 Cognitive need

In the context of the present study, cognitive need refers to students' motivation to use a specific m-learning application that can assist them to acquire information, knowledge, and critical thinking skills (Katz et al., 1973; Mondi et al., 2008). If students can get much useful information and knowledge from the m-learning usage, they will be more likely to actively participate in and involve in the m-learning application. The positive impact of cognitive need on continuance behaviours has been validated by several previous studies (Shi et al., 2010). Therefore, it is reasonable to expect that cognitive need will have a positive influence on m-learning continuance intention. Thus, the following hypothesis is proposed:

Hypothesis 1a A student's cognitive need will positively affect his/her m-learning continuance intention.

3.1.2 Social need

Social need refers to students' motivation to use a specific m-learning application that can help them to collaborate with classmates or instructors during the learning process (Mondi et al., 2008). Social need has been identified as an important factor in determining usage behaviours (Hashim et al., 2015; Wu et al., 2010). Wu et al. (2010) found that social need has a positive influence on online game continuance. Hsiao et al. (2016) also found that social tie positively affects continuance use of mobile social applications. In the context of the present study, m-learning can help students to interact and collaborate with their classmates anytime and anywhere, which fulfil their social need. If a specific m-learning application can help students in making co-creating knowledge, they are more likely to continue using it. Therefore, based on the above discussions, we can hypothesise that:

Hypothesis 1b A student's social need will positively affect his/her m-learning continuance intention.

3.1.3 Affective need

Affective need refers to students' motivation to use a specific m-learning application which can assist them to seek pleasant feelings, emotional fulfilment, and aesthetic experience during the learning process (Mondi et al., 2008). The positive impact of affective need on media usage behaviour has been validated by existing literature (Gan and Wang, 2015; Hashim et al., 2015; Wu et al., 2010). For instance, Hashim et al. (2015) found that adult learners' affective need positively influences their attitude to use m-learning, which determines usage behaviours. Gan and Wang (2015) also found that affective need has a positive influence on WeChat usage. Wu et al. (2010) found that enjoyment need positively affects online game continuance usage. In the context of the present study, students would be more likely to continue use of the m-learning if the usage can satisfy their affective need. Hence, the following hypothesis is developed:

Hypothesis 1c A student's affective need will positively affect his/her m-learning continuance intention.

3.1.4 Entertainment need

Entertainment need refers to students' motivation to use a specific m-learning application for seeking exciting and fun learning resources (Mondi et al., 2008). The positive association between entertainment need and continuance use has been validated by extant studies (Gallego et al., 2016). For instance, Shi et al. (2016) found that entertainment positively affects social media continuance. Similarly, Gallego et al. (2016) also found that entertainment need has a strong and positive influence on continuance use of second life for e-learning propose. Therefore, we can hypothesise that:

Hypothesis 1d A student's entertainment need will positively affect his/her m-learning continuance intention.

3.2 Perceived integration of online and offline learning

The m-learning mode provides students with a ubiquitous and convenient learning environment that changed the way they learn and interact between online and offline learning (Zydney and Warner, 2016). It can allow students to instantly interact and collaborate with classmates and instructors on a lecture's online forum, even when they are attending an on-campus school-based lecture. M-learning thus provides a promising opportunity for students to fulfil their various learning needs by effectively integrating their online and offline learning. Based on extant studies (Delgado-Ballester and Hernández-Espallardo, 2008; Yang et al., 2018, 2016a), the present study defined perceived integration as the strength to which students perceive the online and offline learning as being bonded together by using m-learning.

Previous studies found that perceived integration significantly influence consumers' loyalty intention (Lee and Kim, 2010), retailers' sale growth (Cao and Li, 2015), and mobile government microblogging services (Yang et al., 2018). In the present study, the seamless integration of students' online and offline learning by using m-learning platform would facilitate the frequency of interaction among their classmates and instructors, which lead to repeat usage. Based on extant studies (Lee and Kim, 2010; Yang et al., 2018), we hypothesise that:

Hypothesis 2 A student's perceived integration of online and offline learning will positively affect his/her m-learning continuance intention.

It is reasonable to expect that students' perceived integration of online and offline learning will positively affect their various needs towards m-learning continuance including cognitive, affective, social, and entertainment needs (Lee and Kim, 2010; Yang et al., 2016b). In fact, by integrating online and offline learning, m-learning can help students to better acquire information and knowledge, experience pleasant feelings, interact with classmates, and seek fun learning resources. In the context of the present study, when students form a high level of integration between the online and offline learning by using m-learning platform, their cognitive, affective, social and entertainment needs of using the platform would also be high.

Extant studies have validated the positive correlation between perceived integration and user motivation for using social media (Lee and Kim, 2010; Yang et al., 2016b). For instance, Lee and Kim (2010) found that perceived integration are positively related with consumers' hedonic and utilitarian shopping orientation. Yang et al. (2016b) examined factors that influence social media usage behaviour. They found that perceived integration has a positive influence on users' motivation to strengthen social interaction tie with other social network members. Based on the extant literature (Lee and Kim, 2010; Yang et al., 2016b), we can hypothesise that:

Hypothesis 3 A student's perceived integration will positively affect his/her cognitive need (H3a), social need (H3b), affective need (H3c), and entertainment need (H3d).

3.3 Controlling variables

User experience is widely known to play an important role in regulating use behaviours. As the test bed of our study is a mobile-based learning application, mobile internet experience may affect m-learning usage behaviours. Thus, mobile internet experience and several widely used demographic characteristics such as age, and gender were included in our study as control variables.

4 Methodology

4.1 Instrument

The constructs in the current study were measured with multiple items, which were adapted from the extant literature to ensure content validity. All items were measured on a seven-point Likert scales, with response choices ranging from one (strongly disagree) to seven (strongly agree). Three items of entertainment need were adapted from Mondi et al. (2008). The items of cognitive, social, and affective needs were adapted from Huang and Chiu (2015). The items of perceived integration were adapted from Lee and Kim (2010) and Yang et al. (2016a). Three items of m-learning continuance intention were adapted from Sørebø et al. (2009).

As the original scales were in English, a back-translation procedure was performed to ensure no significant differences between the English and the translated Chinese scales. In addition, two professors who focused on the m-learning research were invited to give their suggestions on the developed scales. Based on their feedback, some items were revised to make the instrument clearer and understandable. The final items and their sources in questionnaire are listed in Appendix A.

4.2 Sample

The empirical data was collected from college students who took mobile-based courses on an online education platform (WANKE, http://www.wanke001.com), which released its m-learning APP in July 2015. Students can reach a plenty of ITs related courses on the WANKE platform, which are originally developed by five universities located in the eastern China. The WANKE platform provides a flipped classroom learning environment that online educational materials (e.g., educational videos and online quizzes) are utilised to replace teachers' offline lectures (Shu and Gu, 2018). Students need to accomplish the designated courses' educational videos and online quizzes in home-based studies, before the corresponding school-based sessions. The school-based teaching time thus can be reallocated to give students unique learning experiences by interacting and collaborating with their classmates and instructors.

Table 1 Sample demographics

Measure	*Item*	*Number (N = 261)*	*Percentage*
Gender	Male	106	40.6%
	Female	155	59.4%
Age	<18 years	3	1.1%
	18~23years	253	96.9%
	>23 years	5	1.9%
Major	Information management	74	28.4%
	Software engineering	46	17.6%
	Electronic commerce	141	54%
Mobile internet experience	<1 year	13	5%
	1~3years	81	31%
	3~5 years	71	27.2%
	>5 years	96	36.8%

Before enrolling in those IT related courses, college students need to register on the WANKE platform first. Then, they can prepare for their classes by learning from the educational videos and online quizzes on the WANKE platform that cover what will be discussed in the school-based classes. Subjects were the first- and second-year undergraduate students who enrolled in the classes of either the fundamentals of computer (FOC) or internet and web design (IWD) provided by a local university. To capture m-learning continuance intention in an online-cum-offline learning context, we ensured that all participants used the WANKE mobile app-based online lecture. A web-based survey was conducted after the initial four weeks of the classes. After scrutinising all responses and dropped those who without m-learning experiences and those who used the same answer for all questions, we collected a total of 261 valid responses (see Table 1). According to participant's self-reports, 59.4% were female. Most of them (96.9%) were aged between 18 and 23. In terms of major, 54% were electronic commerce (EC), 28.4% were information management (IM), and 17.6% were software engineering (SE). In terms of mobile internet use experiences, 5%, 31%, 27.2%, and 36.8% had 1 year or less, 1–3 years, 3–5 years, and 5 years or more use experience, respectively.

5 Data analysis and results

Following the procedures of the extant studies (Chong, 2013; Hew et al., 2016; Liébana-Cabanillas et al., 2017; Sharma et al., 2017), a SEM-neural network method was employed to predict m-learning continuance behaviours. Specifically, SEM will first be used to validate the overall research model, and significant predictors obtained from SEM will be used as input to the neural network model to rank the relative influence.

5.1 Reliability and validity

The internal reliability of the constructs was tested by calculating Cronbach's alpha and composite reliability (CR). As displayed in Table 2, all Cronbach's alpha and CR coefficients were exceed the recommended benchmark of 0.7, indicating good internal consistency (Nunnally, 1978). All average variance extracted (AVE) values were above the suggested threshold of 0.5, suggesting good convergent validity (Gefen et al., 2000).

Table 2 Scale properties

Variable	*Item*	*Standard loading*	*Cronbach's alpha*	*CR*	*AVE*
Cognitive need (CON)	CON1	0.909	0.906	0.941	0.843
	CON2	0.940			
	CON3	0.903			
Affective need (AFN)	AFN1	0.938	0.947	0.967	0.906
	AFN2	0.968			
	AFN3	0.949			
Social need (SON)	SON1	0.928	0.942	0.963	0.897
	SON2	0.957			
	SON3	0.955			
Entertainment need (ENN)	ENN1	0.944	0.940	0.962	0.894
	ENN2	0.939			
	ENN3	0.952			
Mobile learning continuance (MLC)	MLC1	0.961	0.955	0.970	0.917
	MLC2	0.957			
	MLC3	0.954			
Perceived integration of online-offline learning (PINT)	PINT1	0.909	0.908	0.943	0.847
	PINT2	0.943			
	PINT3	0.906			

The discriminant validity was calculated by compared the square root of the AVE of each construct and its inter-construct correlations. As showed in Table 3, the square roots of the AVE for each construct was greater than its corresponding inter-construct correlation coefficients, showing good discriminant validity (Gefen et al., 2000).

An exploratory factor analysis (EFA) with Varimax rotation was conducted to further examine the discriminant validity of the constructs. The EFA results indicated that the internal loading of each distinct factor was higher than its cross-loadings on other factors, showing good discriminant validity (see Appendix B).

Table 3 Factor correlation coefficients and square roots of the AVE*

	Mean	*SD*	*CON*	*SON*	*AFN*	*MLC*	*PINT*	*ENN*
CON	4.889	1.160	*0.918*					
SON	4.498	1.158	0.510	*0.947*				
AFN	4.978	1.119	0.588	0.601	*0.952*			
MLC	5.028	1.264	0.586	0.643	0.802	*0.957*		
PINT	5.315	1.052	0.626	0.461	0.655	0.649	*0.920*	
ENN	5.055	1.143	0.405	0.350	0.490	0.528	0.512	*0.946*

Notes: *diagonal elements are the square root of AVE. These values should exceed the inter-construct correlations for adequate discriminant validity. CON = cognitive need; AFN = affective need; SON = social need; ENN = entertainment need; PINT = perceived integration of online-offline learning; MLC = M-learning continuance.

5.2 Common method bias

The current study performed two statistical analyses to assess the potential common method bias. First, we conducted a Harman's one-factor test as recommended by Podsakoff and Organ (1986). The results demonstrated that seven factors are present and the largest variance explained by a single factor is 16.648%, indicating that common method bias was unlikely a problem in this study. Second, following the procedure recommended by Liang et al. (2007), the present study first builds a new measurement model that all indicators load on a common method factor, and then compared it with the original measurement. The results indicated that the principal variable loadings of the original measurement were all significant at the 0.001 level, while the loadings of the common method factor were all insignificant. This demonstrates that the common method bias, again, was unlikely a threat in our dataset.

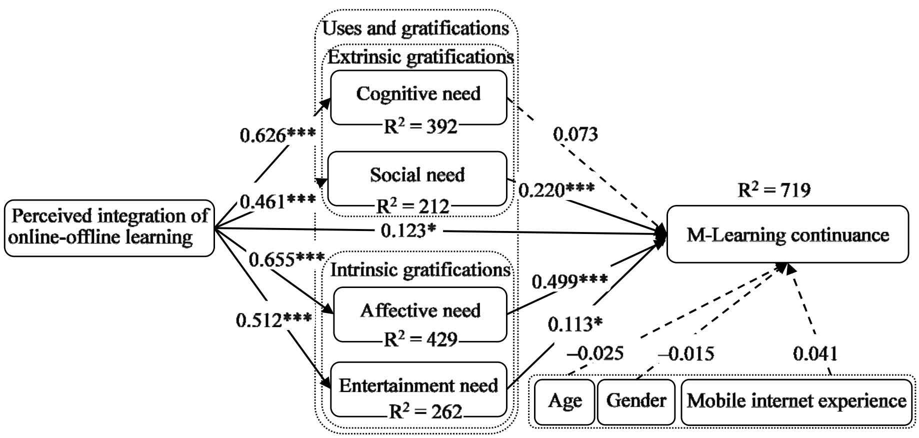
5.3 Hypothesis testing

PLS is a component-based SEM approach that has been widely adopted in the existing literature. Compared with covariance-based structural equation modelling (CB-SEM) methods, PLS has fewer statistical identification issues and does not require critical normal distribution of data. It can also handle both reflective and formative constructs and requests a relatively small sample size for verifying a structural equation model. Also, this component-based method is the preferred tool for studies with the aim for theory development and prediction (Hair et al., 2011). Considering the predicting nature of our study, PLS is more suitable for the model testing in the present study. Smart PLS

2.0 was used to test the structural model equation and corresponding hypotheses, then the bootstrapping procedure was selected for calculating the significance of the path's coefficients.

As displayed in the Figure 2, except hypothesis H1a, other hypotheses are supported by the data. Specifically, the hypothesised paths from social, affective, and entertainment needs on m-learning continuance intention were all significant, validating hypotheses H1b, H1c, H1b. The impact of perceived integration on m-learning continuance intention was significant, thus supporting H2. Four hypothesised paths from perceived integration on cognitive, social, affective, and entertainment needs were all significant at $p < 0.001$ level, validating H3a, H3b, H3c, and H3b. However, the influence of cognitive need on m-learning continuance intention was not significant, thus hypothesis H1a was not supported. We also examined the influences of three control variables on m-learning continuance intention. The results show that the impact of age, gender, and mobile internet experience on m-learning continuance intention were all not significant.

Figure 2 Test results of the research model



Notes: *p < 0.05; ***p < 0.001.

The R^2 for cognitive need, social need, affective need, entertainment need, and m-learning continuance intention were 0.392, 0.212, 0.429, 0.262, and 0.719, respectively. This indicates that our proposed model provides a reasonable explanation of the variance in m-learning continuance.

5.4 Neural network analysis

An artificial neural network is defined as "a massively parallel distributed processor made up of simple processing units, which have a neural propensity for storing experimental knowledge and making it available for use" (Haykin, 1994). In the present study, the multilayer perceptron (MLP) network model was used to train the neural network (Sharma et al., 2017). The neural network was developed using SPSS 22.0, which the four independent significant variables from the SEM analysis (e.g., affective need, social need, entertainment need, and perceived integration) were used as the input layer of the neural network. Considering there is no heuristic approach for identifying the hidden nodes in a neural network, following the procedure recommended by Wang and

Elhag (2007), the neural network was examined using one to ten hidden nodes. The accuracy of the ten neural network models was assessed by using the root mean square error (RMSE). The results show that four hidden nodes were complex enough to measure the data without introducing additional errors to the entire model. A ten-fold cross validation procedure was conducted to avoid overfitting of the network model, whereby 90% of the data was used for training network and the remaining 10% was used for measuring the prediction accuracy of the network (Liébana-Cabanillas et al., 2017).

Table 4 RMSE for neural network model

Network	*Training*	*Testing*
1	0.123	0.128
2	0.119	0.148
3	0.119	0.126
4	0.120	0.212
5	0.128	0.093
6	0.132	0.128
7	0.167	0.133
8	0.123	0.104
9	0.107	0.073
10	0.119	0.120
Average	0.126	0.127
Standard deviation	0.016	0.037

As displayed in Table 4, the average of cross validated RMSE for the training model was 0.126, while the testing model was 0.127. This indicates that our network model is a quite reliable and accurate in forecasting the relationships between predictors and outputs (Chong, 2013; Liébana-Cabanillas et al., 2017).

Table 5 Sensitivity analysis

	Affective need	*Social need*	*Entertainment need*	*Perceived integration*
1	0.307	0.252	0.23	0.211
2	0.331	0.208	0.268	0.193
3	0.385	0.212	0.134	0.269
4	0.346	0.223	0.163	0.268
5	0.358	0.208	0.203	0.23
6	0.269	0.232	0.191	0.308
7	0.326	0.232	0.149	0.294
8	0.36	0.206	0.22	0.214
9	0.289	0.204	0.224	0.283
10	0.349	0.234	0.132	0.286
Average	0.332	0.221	0.191	0.256
Importance (%)	100	66.59	57.65	76.98

Sensitivity analysis performance was then calculated by averaging the importance of the four independent variables in predicting the dependent variable for the ten networks (Chong, 2013). As displayed in Table 5, affective need is the most influencing predictor of college students' m-learning continuance behaviours, followed by perceived integration of online-offline learning, social need, and entertainment need.

6 Discussion

As learners' online and offline learning environments has been increasingly integrated by m-learning platform, it is important to examine m-learning usage behaviours from an online-cum-offline perspective. Based on the U&G theory and literature related to perceived integration, the present study examined the impacts of perceived integration and learning gratifications on college students' m-learning continuance by employed a SEM-neural network method. This research provides several important findings.

First, the results of the present study support the application of the U&G theory in explaining m-learning continuance behaviours. U&G theory posits that people are motivated by a variety of needs and actively seek to fulfil the needs from using the particular media (Gallego et al., 2016). The present study found that college students' social, affective, and entertainment needs positively affect their m-learning continuance. The results are consistent with prior studies on the impacts of various learning gratifications on e-learning usage behaviours (Hashim et al., 2015; Mondi et al., 2008). In terms of path coefficient and significant levels calculated by SEM, affective need exerts the strongest influence on m-learning continuance. This is consistent with the results of the neural network analysis which show that affective need is the most influencing predictor of continuous use of m-learning. This highlights the critical role of affective need, such as pleasant feelings and aesthetic experience, in determining college students' m-learning continuance. Social need also plays an important role in determining college students' m-learning continuance. This suggests that the motivation of interaction and collaboration with other learners is also important for promoting m-learning usage in the post-adoption stage. In addition, it is worthy to know students' entertainment need (e.g., gaining attractive and interesting resources and functions) also facilitate college students' m-learning continuance. However, the impact of cognitive need on m-learning continuance was not significant. One plausible explanation is that with the exponent growth of various learning information and contents fill in the mobile applications markets, there is not a problem for the college students to acquire learning information but how to effectively acquire information and knowledge. Indeed, the various information and contents on mobile devices nowadays have increasingly become a distracter for learners, especially in the last two or three years.

Second, the present study found that perceived integration positively affects college students' extrinsic and intrinsic motivations of using m-learning. This finding therefore provides evidence that the well integration of online and offline learning by using m-learning is important for satisfying students' various needs (Lee and Kim, 2010; Yang et al., 2016b). Specifically, the impacts of perceived integration on college students' cognitive, social, affective, and entertainment needs were all significant at $p < 0.001$. This suggests that educators can fulfil college students' extrinsic and intrinsic needs by effectively integrating their online and offline learning. Indeed, if the m-learning developers can maintain a well-integrated online and offline learning via mobile-based learning platform, students are likely to generate positive motivations on using the m-learning platform. The underlying reason may be that m-learning can enhance students' learning utilities by offering them with accessing and interacting with different learning channels suited to their different needs according to their convenience. For instance, m-learning enables students to take part in an online pre-course discussion with their classmates, when they are travelling on buses or other vehicles.

Third, the present study found that perceived integration not only has indirect influences on m-learning continuance via learning gratifications, but also has a direct influence on m-learning continuance. This is confirmed by the results of the neural network analysis which show that perceived integration is the second largest predictor of m-learning continuance. This thus highlights the important role of perceived integration of online-offline learning in forming students' learning evaluations and behavioural reactions. Due to offline face-to-face classrooms and online-based virtual learning platforms are different in terms of learning process, availability, and flexibility, m-learning developers or educators can enhance students' gratifications and subsequent usage by improving the mobile-based online and offline learning synergies. The present study thus further validated the U&G theory in an online-cum-offline m-learning context.

Finally, in terms of the control variables, the present study found that the influence of mobile internet experience on m-learning continuance intention was not significant. This is consistent with several previous studies which reported that mobile internet experience does not has significant influence on users' service quality perceptions (Kim and Hwang, 2012) and usage behaviours (Yang et al., 2016a). In line with the previous studies (Hew et al., 2016; Yang et al., 2019), the impacts of age and gender on m-learning continuance intention were also not significant.

7 Theoretical and practical implications

7.1 Theoretical implications

The present study provides several implications to literature. First, the existing studies tend to focus on technology-related enablers to explain students' m-learning adoption and usage behaviour by extending and modifying leading IT theories. The underlying mechanisms of why and how students use m-learning to satisfy their various needs are still not clear. In addition, the users of m-learning have dual roles: technology user and service consumer (Kim et al., 2007; Yang et al., 2015). The students of m-learning are service consumers rather than simply technology users. Therefore, the present study aims to examine the factors that affect m-learning continuance from a uses and gratifications-based perspective.

Second, unlike most extant studies examined m-learning behaviours by using SEM method, the present study employed a SEM-neural network method to predict the antecedents of m-learning continuance. By employing the SEM-neural network approach, we can validate the results by using multiple approaches and determine the most significant factors affecting m-learning continuance as well as their relative importance (Chong, 2013; Liébana-Cabanillas et al., 2017).

Finally, extant studies usually regard students' online and offline learning as isolated from each other, and seldom consider the factors that affect m-learning continuance in an online-cum-offline learning context. In the era of mobile internet, learners' online and offline learning environments have been increasingly integrated by m-learning pedagogy. This requires researchers who investigate m-learning usage behaviour look beyond a single learning channel context. The present study contributes to the extant literature by exploring how perceived integration of online and offline learning might affect college students' motivations and consequent continuance using of m-learning.

7.2 Practical implications

The present study also offers several contributions to practice. First, m-learning developers or educators should pay close attention to the learning gratifications because the present study found that college students' social, affective, and entertainment needs positively affect their m-learning continuance. In terms of students' affective need, m-learning developers should maintain a well-designed and attractive user interface of m-learning system (Sarrab et al., 2016). For instance, its layout should be simple and easy to use; its navigation should be intuitive; its elements should be visualised in the same way cross different screen; its media types should be various by including video, audio and text. As for students' social need, m-learning practitioners should also need to embed the mainstream collaborative social network applications (e.g., Sina Weibo, or WeChat) within the m-learning platform. This will allow students to interact and collaborate with peers and instructors in the form of synchronous or asynchronous communication. As for students' entertainment need, m-learning developers or educators should include attractive and exciting resources and functions in their m-learning platform to promote continuance usage. For example, they can introduce the mobile game-based learning functions that can make the learning process more interesting and entertaining.

Second, to promote college students' m-learning continuance, educators should be aware of the different impacts of the learning gratifications on m-learning continuance. First, educators should emphasise the fulfilment of students' affective need because college students are more likely to continue using m-learning if they can acquire aesthetic experience during the usage process. Next then, educators should ensure their m-learning platform can meet students' social need because students' decision on m-learning continuance is also strongly influenced by how the platform can support their social interaction needs. Also, educators should act to meet students' entertainment need because it significantly affects students' m-learning continuance. Unlikely many previous studies focused on the cognitive-based motivations on promoting m-learning usage, the present study examined both extrinsic and intrinsic learning gratifications on m-learning continuance. Our results suggest that to accurately explain m-learning continuance, both the extrinsic and intrinsic learning gratifications should be considered simultaneously. This thus provides more specific instructions for educators to take actions for managing students' m-learning continuance usage.

Finally, m-learning developers and educators should be aware of the critical role of perceived integration on determining students' m-learning continuance in higher education because it exerts strong influences on m-learning continuance via students' affective, social, and entertainment needs. By maintaining a mobile-based learning platform that effectively integrated online and offline learning, m-learning developers and educators can enhance students' learning gratifications which will further affect their m-learning continuance. For m-learning developers and educators who want to promote students' long-term use of m-learning, they should take measures to improve the synergy and complementarity between online and offline learning channels. For instance, they can provide consistent learning information and materials, flexible selection of learning channels, and collaboration learning functions on their m-learning platform. M-learning developers can also deliver personalised educational contents to students by employed a push and pull combination strategy (Motiwalla, 2007) which may enhance students' online and offline learning integration perceptions.

8 Conclusions

Based on the U&G theory and literature related to perceived integration, this study investigated the determinants of m-learning continuance from an online-cum-offline learning perspective. The results confirm the usefulness of the U&G theory and perceived integration in explaining students' m-learning continuance and identify the positive effects of perceived integration on extrinsic and intrinsic learning gratifications evaluation and subsequent continuance behaviours.

Like all other empirical studies, the results of the present study should be interpreted with some caution. First, it is worth noting that the sample of this study was collected from students related to a single m-learning platform in a single country (e.g., China). While focusing on one platform in a specific region can minimise unexplained variances in the model estimation, such narrow focus might impede the generalisability of our results. Future studies thus can extend our research model by testing our findings in different m-learning platforms and culture contexts.

Second, to better capture the antecedents of learners' continuance behaviours, an ideal research design would be a combination of the survey-based study and the archival data-based analysis. However, the nature of our survey-based approach restricts such cross-method analyses. Future research can employ a combination method to test the factors that affect m-learning continuance.

Third, another potential limitation is that our research did not incorporate actual use behaviours in the research model. Although this limitation is pointed out, it should not undermine our results, as the causal relationship between intention and behaviour has been verified through extensive empirical research (e.g., Venkatesh and Davis, 2000). However, as different intention measurements may still affect the predictive power, future studies are encouraged to offer more insight by including the actual usage behaviour in their research model.

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Appendix A

Scales and items

1 Affective need [adapted from Hashim et al. (2015)]
- AFN1: I like showing my friends how to use WANKE m-learning app in different ways.
- AFN2: WANKE m-learning-based courseware layout, animation and illustrations are good to look at.
- AFN3: I enjoy learning using the WANKE m-learning app.

2 Cognitive need [adapted from Hashim et al. (2015)]
- CON1: I use WANKE m-learning app to acquire new learning information.
- CON2: I carry out online learning resource search through my WANKE m-learning app to answer questions coming from class discussions.
- CON3: I use WANKE m-learning app to explore topics of interest beyond my normal school assignment.

3 Social need [adapted from Hashim et al. (2015)]
- SON1: I use social network services on WANKE m-learning app to interact with my friends.
- SON2: WANKE m-learning app prepares me to join the extended learning community outside the class.
- SON3: Using WANKE m-learning app improves my ability to communicate with other learners.

4 Entertainment need [adapted from Mondi et al. (2008)]
- ENN1: I like the background music and sound effects on the WANKE m-learning courseware, they make learning fun.
- ENN2: I find educational websites on WANKE m-learning app to be interesting
- ENN3: It is fun to experiment with WANKE m-learning app.

5 Perceived online-offline learning integration by using mobile learning [adapted from Lee and Kim (2010) and Yang et al. (2016a)]
- PINT1: WANKE m-learning app allows me to interact with the online learning systems, when I participated in the offline learning activities.

- PINT2: WANKE m-learning app effectively integrated my online and offline learning activities.
- PINT3: WANKE m-learning app effectively mitigated the conflicts (e.g., time conflict) between my online and offline learning activities.

6 Mobile learning continuance [adapted from Sørebø et al. (2009)]

- MLC1: I intend to continue using WANKE m-learning app in the following semester, rather than discontinue its use.
- MLC2: If I could, I would like to continue my use of WANKE m-learning app in the following semester.
- MLC3: My intentions are to extend my use of WANKE m-learning app in the following semester.

Appendix B

Loadings and cross-loading

Factor	*SON*	*ENN*	*CON*	*AFN*	*PINT*	*MLC*
SON1	*0.864*	0.115	0.174	0.219	0.174	0.107
SON2	*0.868*	0.114	0.218	0.190	0.136	0.208
SON3	*0.867*	0.134	0.169	0.186	0.104	0.268
ENN1	0.150	*0.871*	0.141	0.158	0.220	0.119
ENN2	0.134	*0.903*	0.125	0.120	0.099	0.155
ENN3	0.063	*0.891*	0.123	0.163	0.219	0.155
CON1	0.177	0.212	*0.826*	0.171	0.283	0.012
CON2	0.184	0.052	*0.844*	0.195	0.251	0.226
CON3	0.236	0.181	*0.781*	0.177	0.174	0.241
AFN1	0.244	0.177	0.220	*0.760*	0.223	0.344
AFN2	0.268	0.212	0.240	*0.786*	0.283	0.260
AFN3	0.288	0.215	0.215	*0.761*	0.269	0.269
PINT1	0.162	0.190	0.246	0.177	*0.815*	0.167
PINT2	0.203	0.205	0.282	0.221	*0.767*	0.282
PINT3	0.107	0.248	0.236	0.263	*0.787*	0.127
MLC1	0.269	0.269	0.222	0.403	0.256	*0.703*
MLC2	0.333	0.199	0.203	0.346	0.258	*0.738*
MLC3	0.321	0.254	0.226	0.346	0.239	*0.711*
Eigenvalues	2.997	2.931	2.650	2.609	2.602	2.226
Variance %	16.648	16.285	14.721	14.497	14.457	12.366
Cumulative	16.648	32.933	47.654	62.151	76.608	88.974