Kashive and Phanshikar
Smart Learning Environments (2023) 10:34
https://doi.org/10.1186/s40561-023-00253-x

Smart Learning Environments

RESEARCH Open Access

Understanding the antecedents of intention for using mobile learning

Neerja Kashive[1*] and Dharini Phanshikar[1]

*Correspondence:
nirja.kashive@ves.ac.in

[1] VES Business School, 495-497, Near Municipal School, Collector's Colony, Chembur, Mumbai 400074, India

Abstract

This study aimed to identify the factors, which affect the continuance of mobile learning. The study has looked at epistemological, social, and security risk factors based on Magsayo (Interact Technol Smart Educ 20(2):177–208) and how they affect the perceived functional benefits (PFB) and perceived learner value (PLV). Further locus of control and self-efficacy are two personal factors that are investigated in the study to understand mobile learning acceptance continuance. 260 respondents of the study were students and professionals from India who have used mobile for learning. Based on previous research, hypotheses were formulated and tested empirically by building a model using smart PLS structure equation modeling. It was observed that epistemological, security risk and social factors did affect the computer self-efficacy and locus of control of the learners. Epistemological and social factors do contribute to developing PFB and PLV leading to higher mobile learning acceptance continuance. PFB and PLV also showed mediating effects. Based on Magsayo's (2023) previous work, the study has a unique contribution in showing that epistemological and social factors along with security risk do help in developing PFB and PLV leading to higher mobile learning acceptance continuance. These findings can help us understand ways to the development of mobile learning content and context for higher impact.

Keywords: Mobile learning acceptance continuance, Epistemological, Social, Security risk, Perceived functional benefits, Perceived learner value

Introduction

Recent COVID-19 has encouraged many people to learn online as it provides a lot of flexibility by using appropriate technology as suggested by Ched (2020). Mobile learning is catching up fast due to time constraints and the amount of flexibility needed by the learner. Many countries including India have improved their connectivity and availability of Wi-Fi on mobiles. The use and acceptability of mobile phones have gone to the grassroots in India. When discussing mobile learning is defined as "using mobile technologies to facilitate learning" (Hwang & Tsai, 2011) and as "any educational provision where the sole or dominant technologies are handheld or palmtop devices"(Park et al., 2012). There is a lot of research work done to understand mobile learning concerning readiness (Camilleri & Camiller, 2019) and acceptance of this platform for learning (Mittal & Alayo, 2020), and the intention to learn (Watjatrakul, 2016). The uncertainty of a continuance of the pandemic has proposed many advantages for this mode of learning yet not much research has occurred in this area (Crompton & Burke, 2018).

As expected, many theories have been used in the context of mobile learning (M-Learning) i.e., technology acceptance model (TAM), the theory of planned behavior (TPB), personality theories, mobile service acceptance model (MSAM), mobile innovation resistance (MIR), use and gratification theory (UGT), unified theory of acceptance and use of technology (UTAUT) and task-technology fit (TTF). Studies have based their work either on one or a combination of these theories to explain various aspects of mobile learning M-Learning like usefulness, enjoyment, innovation, social aspects, and personality traits. Still, there is a need to understand and develop a more holistic model for M-learning, which would focus on mobile learning adoption and continuance. The areas to look into could be the perceived value put on M-learning (Crompton & Burke, 2018) and the individual factors like the locus of control and computer self-efficacy. Age and gender differences may also play important role in adopting mobile learning (Wang et al., 2009).

In the context of mobile learning, many theoretical frameworks have been applied like the technology acceptance model (TAM) (Bagozzi, 2007; Poong et al., 2017; Qashou, 2021; Saroia & Gao, 2019; Shortfuzzaman et al., 2019) and other used TAM along with Hofstede model (Bojorquz et al., 2016), TTF (Leong et al., 2018) and TPB (Hsia, 2014). UTAUT has also been used extensively to understand mobile learning (Fagan, 2019; Kumar & Bervell, 2019; Sidik & Syafar, 2020). Some studies have used UGT (Hashim et al., 2015) and TBP (Fatima et al., 2019) while others have focused on MIR (Kim et al., 2017) and MSAM (Almaiah, 2020; Hamidi & Chayoshi, 2018).

All these studies have some common factors that emerged from their research like the functional benefits aspects of using mobile learning, which includes usefulness, performance expectancy, etc. Others have explored the affective aspect like enjoyment, hedonic motivation, and affective need for a learner. But few have seen the social influence aspect look into social needs, image, norms, etc. Other less explored aspects may be the security risk (perceived security) and epistemic curiosity (Learning new technology). These factors may be very relevant for a learner while learning through mobile learning. The perceived learner value aspect of how a learner perceives and put value is yet another factor that may need to be investigated to understand how it affects mobile adoption in learners. Some studies have looked into the factors like learners' recommendations (Briz-Ponce, 2017) and attitudes (Fatima et al., 2019; Hashim et al., 2015; Qashou, 2021; Yeap et al., 2016) and their effect on user intention to adopt M-learning. Personality traits like the locus of control and computer self-efficacy may play a critical role in the relationship between perceived learner value and mobile adoption and mediate or moderate the relationship and hence need to be investigated. Mittal and Alavi (2020) developed a teachers' mobile learning acceptance questionnaire, which found nine factors like perceived usefulness, ease of use, self-enhancement, a technological barrier, constructive belief, attitude, and intention to measure the acceptance of the use of mobile in higher education. Self-enhancement and constructive belief were the two new factors identified in the study.

Magsayo (2023) conducted the study and showed that the locus of control moderated the relationship between perceived learner value and perceived functional benefit and mobile learning acceptance continuance. When dealing with specific aspects of mobile learning, they could only find the security risk to be significant in the given model built. The current research has extended the work of Magsayo (2023) and added computer self-efficacy along with internal locus of control as personality traits along with perceived functional benefit (PFB) and perceived learner value (PLV) to understand mobile acceptance continuance. Further, the study included epistemological and social factors as the antecedent of mobile learning and found they significantly affect both PLB and PLV. The study has raised the following research questions to understand the antecedents of intention to continue M-learning (mobile learning).

RQ1: Do epistemological, social, and security risk factors affect internal factors (locus of control and computer self-efficacy) leading to higher perceived functional benefits (PFB) and perceived learner value (PLV)?

For answering RQ1, hypotheses H1(a, b, c and d), H2(a, b, c and d), and H3(a, b, c and d) were suggested and tested through direct effect.

RQ2: Does locus of control and computer self-efficacy affect perceived functional benefits (PFB) and perceived learner value (PLV) and mediate the relationship between epistemological, social, and security risk factors and PFB and PLV?

For answering RQ2, hypotheses H4(a and b) and H5(a and b) were suggested, and the mediation effect was tested through indirect effect.

Literature review

Perceived learner value in M-learning

Perceived learner value (PLV) shows how a learner perceives the value gained from their learning experience when using Mobile learning. This construct can be related to Luttrell and Richard's (2011) concept of how learners in higher education value their education and this may be caused due by different factors like first their enjoyment or satisfaction due to higher engagement levels. Second, its utility to achieve their long-term and short-term goals, and third, their overall learning from the M-learning module. The fourth perceived cost of losing other activities when engaging in learning activities and the fifth is the external expectations like family and friends' expectations that a learner is fulfilling by taking up mobile learning. PLV may relate to the cognitive aspect of using M-learning as a learning mode and it may facilitate learning by providing correct and quality information to add value (Hashim et al., 2015). PLV can also be related to its relevance and compatibility in education during academics (Saroia & Gao, 2019).

Perceived functional benefit in M-learning

Perceived function benefits (PFB) refer to the functional requirements a product or service offers, which may include cost, time, performance, and efficiency provided by technology over face-to-face teaching (Almaiah et al., 2020; Bashir et al., 2020). M-learning use (utilitarian) includes usefulness, performance expectancy, and the advantage of using technology, and its relation to the adoption of M-learning has been studied by many researchers (Bohm & Constantine, 2016; Cheng, 2015). Another functional benefit could be the flexibility gained using M-learning (Bere & Rambe, 2016) and its benefit to the learner in terms of completion of their tasks on time, improved productivity, and becoming more useful (Al-Adwan et al., 2018; Shukla, 2021; Venkatesh et al., 1996).

PFB can then be related to the amount of academic performance enhanced using mobile learning (Davis, 1989). Several studies have shown that functional benefits do affect directly (Hao et al., 2017; Pramana, 2018) and indirectly (Fatima et al., 2019; Yeap et al., 2016) the overall mobile learning adoption.

Personal factors

i. Locus of control

Factors that affect mobile learning performance include the internal locus of control linked to self-management, autonomy, and innovativeness. learners who require autonomy or are internally driven may more often opt for mobile learning (Masrek & Samadi, 2017) as they will have the freedom to choose the process of learning as per their needs (Bohm & Constantine, 2016; Yeap et al., 2016). Any learner's high innovativeness is also internally controlled and can be a crucial factor for M-learning adoption (Iqbal & Bhatti, 2017; Kim et al., 2017; Milosevic et al., 2015), especially in the informal learning process (Karimi, 2016). Locus of control influences ease of use, usefulness, and behavior control leading to a higher intention for learning by using mobile (Hsia, 2014). Hence, these studies lead us to see the importance of personal characteristics as a factor influencing the learner to learn through M-learning. It is shown that learners with an internal locus of control would have higher chances of mobile learning adoption continuance,

ii. Computer self-efficacy

In an Information Technology (IT) context, computer self-efficacy is the individual's capacity to use a computer in a different situation (Compeau & Higgins, 1995) and it's the assessment of one's ability to perform complex tasks on the computer (Compeau & Higgins, 1995). Hence, computer self-efficacy decides the perception of individual ease of use of IT (Hayashi et al., 2004; Roca et al, 2006). Self-efficacy theory can be used to explain this effect (Bandura et al., 1977; Bandura, 1985) as self-efficacy is nothing but individual confidence to take up any specific task including learning by using a computer (Barling & Beattie, 1983). When applied in an e-learning context, learners with high computer self-efficacy will be more interested in trying e-learning and facing difficulties while using e-learning while those with low computer self-efficacy may find it difficult to cope with any complex task and lose interest quickly and may not continue e-learning Compeau & Higgins, 1995) modes including M-learning. Research has shown that computer self-efficacy does affect the perceived ease of use of e-learning (Gong et al., 2004; Ong & Lai, 2006; Terzis & Economides, 2011). Hence, we can propose that computer self-efficacy does affect the perceived functional benefits.

Environmental factors

i. Perceived epistemic curiosity

Perceived epistemic curiosity is defined as the "drive to know" as given by the theory of human curiosity (THC) by Berlyne (1954). Further, Litman and Spielberger (2003) described it as the tendency of an individual to try new ideas, search for solutions to problems and understand the underlying phenomenon. In the context of an online game, it could be an activity that leads to the experience of learning new things, strategies, and trends (Koo, 2009). It may be referred to as any service that increases curiosity and helps in achieving satisfaction by acquiring new knowledge (Sheth et al., 1919). Hence, perceived epistemic curiosity maybe some part of enjoyment or playfulness (Hwang & Fu, 2019; Karimi, 2016). This is further supported by findings that mobile phone usage in class is related to acquiring new knowledge (Olufadi, 2015), and the use of advanced technology like M-learning may lead to higher curiosity among learners (Abdullah et al., 2017; Deng et al., 2004). Still, there is a need to understand this aspect in various settings and consider moderators who help in the relationship between epistemic curiosity and mobile adoption among learners.

Hence, the perceived epistemic curiosity of the learner may lead to higher perceived function value benefits and learner value as it may add to generate new ideas quickly as a lot of information is available very quickly through M-learning. This can help the learners to acquire new, convenient, and effective ways of getting knowledge about the topic of their interest and can also be extended to mobile learning adoption (Crompton et al., 2022; Fatima et al., 2019; Thongsri et al., 2018, 2019; Shukla, 2021). We propose that epistemic curiosity will lead to higher self-efficacy and locus of control leading to higher perceived function benefits and learner value:

H1a Perceived epistemic curiosity of learners affects Computer Self-Efficacy toward mobile learning among learners.

H1b Perceived epistemic curiosity among learners affects the locus of control toward mobile learning among learners.

H1c Perceived epistemic curiosity of learners affects perceived functional benefit toward mobile learning among learners.

H1d Perceived epistemic curiosity of learners affects Perceived learner value toward mobile learning among learners.

ii. Perceived security risks

Perceived security risk suggests the learner's perception of data security and privacy are in place for any electronic transaction like online authentication needed as identity proof (Almaiah et al., 2020). It may also be related to the process adopted by mobile learning systems to safeguard learners' personal information from any cyber-attack (Almaiah et al., 2020). This may be relevant for M-learning for creating passwords and privacy issues related to privacy and integrity (Jia et al., 2012). This determination can also be related to gaining trust from learners regarding the privacy and security aspects of the system and it is seen from findings that a low level of perception about security risk may lead to a lower level of mobile learning usage (Al-Adwan et al, 2018). Security risk has a direct relationship with the intention to use M-learning (Al-Adwan et al., 2018; Almaiah et al., 2020; Hamidi &Chvosshi, 2018) and indirect effect (Nikou & Economides, 2017; Obiria & Kimwele, 2017). Hence, security risks may lead to lower mobile adoption among learners. The research has shown either positive or negative links between security risk and intention to use M-learning through ease of use and usefulness (Nikou & Economides, 2017; Sabah, 2016) or perceived value. Security risk can negatively impact mobile adoption continuance and hence following relations have been proposed:

H2a Perceived Security Risk of learner affects Computer Self-Efficacy toward mobile learning among learners.

H2b Perceived Security Risk of learner affects the locus of control toward mobile learning among learners.

H2c Perceived Security Risk of learner affects Perceived functional benefit toward mobile learning among learners.

H2d Perceived Security Risk of learner affects Perceived learner value toward mobile learning among learners.

iii. Perceived social influence

Perceived social influence generally occurs at three levels due to compliance with some groups, identification leading to self-satisfying relationships, and internalization by finding it rewarding internally (Kelman, 1958). Other studies have related to how "important others" view you when adopting new technology like mobile learning (Venkateash et al., 2003). Hence social norms and images and lectures' expertise and acceptance of mobile learning do influence students adopting M-learning (Badwelan et al., 2016; Milosevic et al., 2015). The learner would adopt M-learning much faster when this medium of learning can help achieve their interaction and social needs (Hashimi et al., 2015). The learner may be forced to use mobile learning when he/she is made to learn through technology-enabled learning platforms (Kumar & Bervell, 2019), or the usage of M-learning becomes critical as performance becomes high by using M-learning (Fagan, 2019).

Many studies (Padilla-Melendez et al., 2008; Pramana, 2018; Sanchez-Prieto et al., 2019; Shukla, 2021; Sidik & Syafar, 2020; Yeap et al., 2016) have shown that perceived social influence does affect M-learning adoption due to acceptance by the peer group due to popularity leading to high-status symbol. These may be linked to identification and internalization with similar others and a positive effect is seen on mobile adoption. Others have seen indirect effects through usefulness and ease of use (Fagan, 2019; Nikou & Economides, 2017; Pramana, 2018). Hence, the following relationship can be proposed:

H3a Perceived social influence of the learner affects computer self-efficacy toward mobile learning among learners.

H3b Perceived social influence of a learner affects the locus of control toward mobile learning among learners.

H3c Perceived social influence of the learner affects perceived functional benefit toward mobile learning among learners.

H3d Perceived Social Influence of learner affects Perceived learner value toward mobile learning among learners.

Computer self-efficacy and mobile learning adoption

Computer self-efficacy can be explained through social cognitive theory (SCT), which states that any individual is affected by self-efficacy that decides if they will take up a task, the amount of effort they will put and the level of persistence they will showcase while doing that task (Bandura, 1977). Hence, computer self-efficacy will decide the completion of learning using the computer. A learner with high computer self-efficacy may use the computer to complete a complex task and feel good about having high computer competence as this may also lead to higher intrinsic motivation (Deci, 1975; Deng et al., 2004). This may hold good even in the E-learning context as it showcases computer mastery. Previous studies have shown that computer self-efficacy does affect the intention to use e-learning (Hu et al., 2003; Tung & Chang, 2008), and hence the following hypothesis is proposed:

H4a Computer Self-Efficacy of learner affects Perceived functional benefit among mobile learner.

H4b Computer Self-Efficacy of learner affects Perceived learner value among mobile learner.

Locus of control and mobile learning adoption

Individuals who are high on internal locus of control are always looking for relevant and critical information to complete any task and they are willing to explore new technology or methods to improve their knowledge gain leading to higher outcomes (Leftcourt, 1982; Spector, 1982). Many studies have highlighted the link between internal locus of control and mobile learning adoption (Fatima et al., 2019; Kim et al., 2017; Kumar & Bervelle, 2019; Qashou, 2021; Sidik & Syaafar, 2020) and showed the relationship between self-efficacy, personal characteristics, innovativeness, and other features linked to an internal locus of control affecting the mobile learning intentions. Hsai (2016) has seen the positive effect of internal locus of control on ease of use, usefulness, and behavioral control on the intention to use e-learning. Hence, the study proposes that locus of control may affect perceived functional benefit and perceived value leading to higher mobile adoption, and the following hypotheses are proposed:

H4c Locus of control of the learner affects Perceived functional benefit among mobile learners.

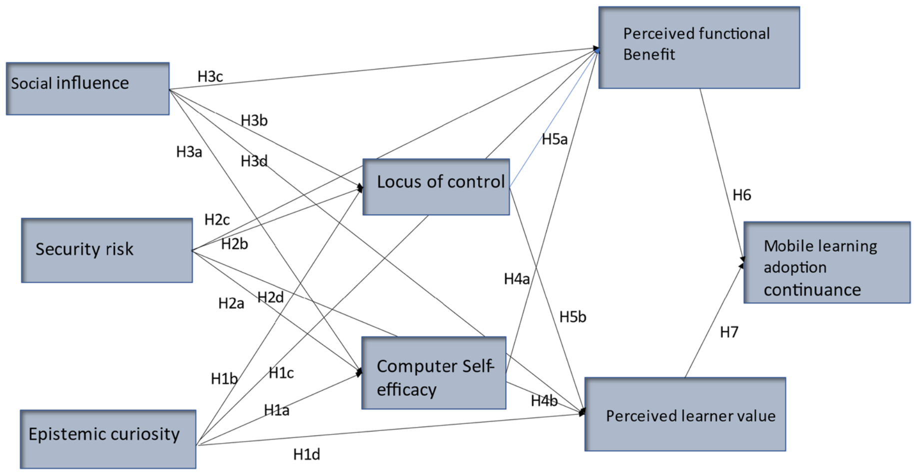

Fig. 1 Conceptual model for mobile learning adoption

H4d Locus of control of the learner affects Perceived learner value among mobile learners.

Perceived functional benefits and mobile learning adoption

The perceived functional benefit refers to the level of usefulness, performance, and efficiency perceived by the user, and a positive direct link is seen between perceived functional benefit and learner intention to use e-learning (Almaiah, 2020; Fagan, 2019; Hao et al., 2017; Hsia, 2016; Kim et al., 2017; Kumar & Bervell, 2019; Leong et al., 2018; Pramana, 2018; Qashou, 2021; Sabah, 2016; Sanchez-Prieto et al., 2019; Saroia & Gao, 2019; Shukla, 2021; Sidik & Syafar, 2020; Thongsri et al., 2018)., some researchers have shown an indirect effect through other factors like attitude and mobile learning resistance (Briz-Ponce et al., 2017; Fatima et al., 2019; Qashou, 2021; Saroia & Gao, 2019). Hence, the following hypothesis can be proposed:

H5 Perceived functional benefit is positively related to the Mobile Learning adoption among mobile learners.

Perceived learner value and mobile learning adoption

Perceived learner value can be referred to as the learner's ability to focus more on the study and achieve a high level of success (Luttrell & Richard, 2011). Learners perceive high value from learning when they are more engaged or involved in learning compared to the traditional way of learning (Gallarza et al., 2017). Thus, learners with higher perceived learner value will be associated with a higher level of mobile adoption.

H6 Perceived learner value is positively related to Mobile Learning adoption among mobile learners.

Research model

The above comprehensive literature review and proposed hypothesis lead to the proposed conceptual model as shown in Fig. 1. The conceptual model is created by hypothesizing the various relationships between environmental and personal factors and perceived learner value and perceived functional benefit and their effect on overall mobile learning adoption continuance. Furthermore, the conceptual model is tested empirically by structural equation modeling (SEM) using Smart PLS.

Research design

Samples and procedure

The data was collected from 260 students and professionals residing in India who have ever learned through mobile. For data collection, 45 min slots were taken for a batch of 30 respondents. The aim and objective of the study were explained to the participants, and they were promised to maintain complete anonymity. It was explained to them that this study and its results will be solely used for academic purposes and to enhance understanding of the intention to use mobile for learning. The forms were circulated in hard copy and only 180 responses were received. Further Google form was created and circulated to working professionals and data was collected from 80 respondents.

The questionnaire had two sections that first captured the demographic profile of respondents concerning their gender, age, qualification, occupation, years of experience, designation, and the number of hours spent on mobile learning in a week.

The second section consisted of specific questions related to M-learning. The mobile learning adoption was captured by perceived learner value and perceived functional benefit. These factors were further tested for their effect on environmental factors like epistemic curiosity, social influence, and security risk. and personal factors like the locus of control and self-efficacy.

It was observed that out of 260 respondents, 54.6% were male and 45.4% were female. The age-wise distribution was 74.6% from the age group between 20 and 25 years, 11% between 26 and 30 years, and 15% above 31–40 years. Education wise 2.3% were diploma, 45.4% were graduates and 52.3% were postgraduates. The sample consisted of 30.4% professionals and 69.6 students, with 70% having 0–3 years of experience and 30% having 4–7 years of experience.72% were from the junior level and 28% were from the middle level. When asked about the number of hours spent in a week learning on mobile platforms 61.9% spent 2–5 h while 38.1% spent between 6 and 10 h.

Measures

Perceived epistemic curiosity (PEC) was adapted from the various scales available in previous literature (Liu et al., 2010; Fatima et al., 2019; Shukla, 2021; Thongsri et al., 2018). Four items were used to measure PEC with sample item as "I find using mobile learning allows experimenting with new ways to access and share information".

Perceived security risk (PSR) was adapted from the various scales available in previous literature (Almaiah, 2020; Hamidi & Chavoshi, 2018; Nikou & Economides, 2017; Sabah, 2016). PSR was measured using four items and sample items as "When I use mobile learning, it will prevent associating with a high potential data loss".

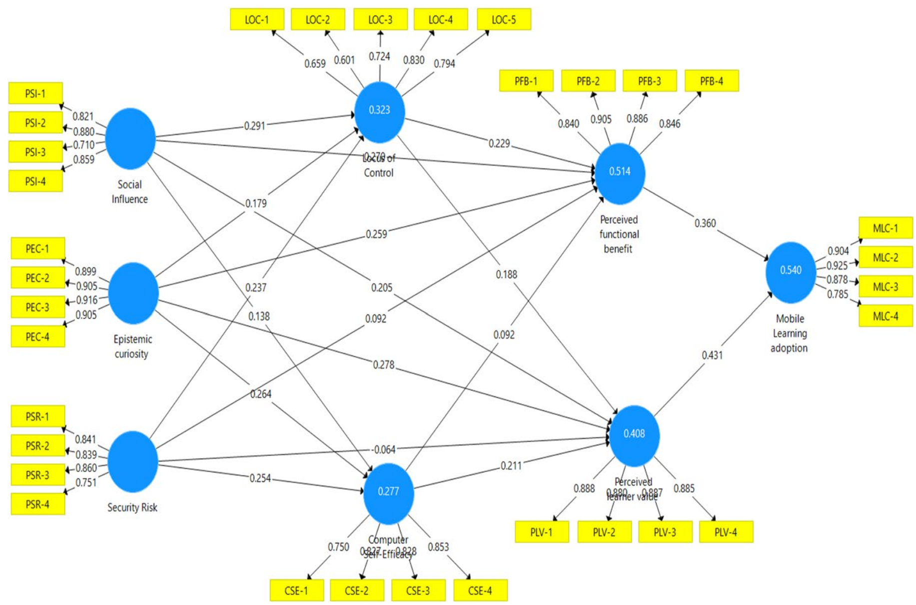

Fig. 2 Smart PLS-SEM model for Mobile Learning Adoption model

Perceived social influence (PSI)) was adapted from the various scales available in previous literature (Briz-Ponce et al., 2017; Pramana, 2018; Sanchez-Prieto et al., 2019; Shorfuzzaman et al., 2019; Shukla, 2021; Sidik & Syafar, 2020). PSI was again measured by four items and a sample item as "I find that using mobile learning gains a status symbol (i.e.popularity)".

Computer self-efficacy was measured by four items adapted from Compeau and Higgins (1995) and Hsia et al., 2014 study. SE was measured through four items and a sample item as “When I use mobile learning, I learn if there was no one around to tell me what to do as I go”. Locus of control was measured using a five-item adapted from (Hsia et al., 2014). The sample items used as “When I make plans, I am almost certain that I can make them work” and “It is impossible for me to believe that chance or luck plays an important role in my life”.

The perceived learner value (PLV) scale was based on (Gallarza et al., 2017; Luttrell & Richard, 2011). PLV was measured with four items and sample items as “I find using mobile learning… “allows me to get more involved with my learning activities” and “increases interest in studying anytime, anywhere necessary”.

Perceived functional benefit (PBF) was adapted from (Al-Adwan et al., 2018; Badwelan et al., 2016; Hassan et al., 2015; Shukla, 2021). PBF was measured by four items and sample items as “I find that using mobile learning... “improves academic performance” and “accomplishes learning activities more quickly”.

Mobile learning adoption continuance (MLAC) was based on the scales (Almaiah, 2020; Kim et al., 2017; Kumar & Bervell, 2019; Leong et al., 2018). MLAC was measured by four items and sample items as “I intend to continue using mobile learning in the future” and “I prefer to continue using mobile learning over other mediums”.

Results

The Smart PLS-SEM model was built as shown in Fig. 2, for the mobile adoption model. As per Hair et al., 2017) partial least square modeling (PLS-SEM) is most suitable for the situation where there is a need to develop. It is an appropriate method for complex and novel models. Hence, many researchers suggest that PLS-SEM can be used for theory generation rather than for theory confirmation (Urbach & Ahlemann, 2010). some others have suggested using it for testing moderation and mediation effects for complex models (Fassot et al., 2016). The advantage of PLS-Sem is that it does not need the usual assumption of normality and can be applied to small samples as it is based on covariance (Hair et al., 2014). As the current study is testing different antecedents of M-learning adoption and added a completely new construct to test the M-learning continuance with mediation effect PLS-SEM methods were adopted.

As the study has used a self-reporting survey as a method to gather the data from the respondent's testing of common methods, bias becomes important. Firstly concerning confidentiality for data collection, the responses were taken anonymously. Secondly, each construct was measured through multiple items loaded separately on different constructs, and the reliability and discriminate validity of the items were tested.

Lastly, all the items were loaded on a common method latent variable and it was seen that items did unload on a single factor when tested for the Harman single-factor (Podsakoff et al., 2003) and there was no convergent found. Also, when collinearity was tested, all VIF values were less than 3.00 and there was no collinearity effect observed (Kock, 2015).

It was seen that all items loaded well on their respective construct and loadings greater than 0.60 were accepted as shown in Table 1. No item was dropped from any construct in the given model. For model assessment, when testing the reliability and validity, Cronbach alpha values were greater than 0.77 and the composite reliability of the constructs was greater than 0.84. The average variance extracted (AVE) which is a measure of construct convergent validity, was higher than 0.50 and below the acceptable value (Hair et al., 2014) as shown in Table 2**.**

Finally, the discriminate validity was checked as the square roots of AVEs were all greater than the inter-construct correlation values and further, the loadings for all indicators were greater than cross-loadings as seen in Table 3.

After the above assessment model was validated, the measurement model was tested by running the non-parametric bootstrapping with sample (1000). The model fit values showed a good fit with SRMR for the saturated model as $0.062 < 0.08$ and the Chi-square value was high (1180.87 and an NFI value was 0.808.

R-square values provide the predictive power of an endogenous construct, and the R-square value for computer self-efficacy (0.277) and locus of control (0.323) was observed and explained by the three factors considered under study i.e. epistemological, social, and security risk factors. R-square values for Perceived functional benefit (0.514), Perceived learner value (0.408), and Mobile Learning adoption (0.540). Hence, the model could explain the 54.0% variance in the dependent variable Mobile learning continuance, which is quite a good explanation.

Table 1 Factor loadings for all the items for Mobile learning adoption model

	Computer self-efficacy	Epistemic curiosity	Locus of control	Mobile learning adoption	Perceived functional benefit	Perceived learner value	Security risk	Social influence
CSE-1	0.750							
CSE-2	0.827							
CSE-3	0.828							
CSE-4	0.853							
LOC-1			0.659					
LOC-2			0.601					
LOC-3			0.724					
LOC-4			0.830					
LOC-5			0.794					
MLC-1				0.904				
MLC-2				0.925				
MLC-3				0.878				
MLC-4				0.785				
PEC-1		0.899						
PEC-2		0.905						
PEC-3		0.916						
PEC-4		0.905						
PFB-1					0.84			
PFB-2					0.905			
PFB-3					0.886			
PFB-4					0.846			
PLV-1						0.888		
PLV-2						0.88		
PLV-3						0.887		
PLV-4						0.885		
PSI-1								0.821
PSI-2								0.880
PSI-3								0.710
PSI-4								0.859
PSR-1							0.841	
PSR-2							0.839	
PSR-3							0.86	
PSR-4							0.751	

Table 2 Reliability values for the constructs for Mobile learning adoption model

	Cronbach's Alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Computer self-efficacy	0.831	0.836	0.888	0.665
Epistemic curiosity	0.928	0.928	0.948	0.821
Locus of control	0.778	0.796	0.846	0.528
Mobile learning adoption	0.897	0.907	0.929	0.765
Perceived functional benefit	0.892	0.893	0.925	0.756
Perceived learner value	0.908	0.91	0.935	0.784
Security risk	0.841	0.843	0.894	0.679
Social influence	0.837	0.86	0.891	0.673

Table 3 Discriminate validity for the constructs for Mobile learning adoption model

	Computer self-efficacy	Epistemic curiosity	Locus of control	Mobile learning adoption	Perceived functional benefit	Perceived learner value	Security risk	Social influence
Computer self-efficacy	0.815							
Epistemic curiosity	0.436	0.906						
Locus of control	0.458	0.417	0.726					
Mobile learning adoption	0.454	0.463	0.378	0.875				
Perceived functional benefit	0.452	0.561	0.552	0.671	0.870			
Perceived learner value	0.469	0.518	0.471	0.691	0.720	0.885		
Security risk	0.43	0.422	0.449	0.325	0.47	0.324	0.824	
Social influence	0.381	0.473	0.487	0.505	0.583	0.478	0.468	0.820

Table 4 Hypothesis testing for Mobile learning adoption model (direct Effect)

	Original Sample (O)	T Statistics (|O/STDEV|)	*P* Values	Results
H1a: Epistemic curiosity—>Computer Self-Efficacy	0.264	4.312	0	Supported
H1b:Epistemic curiosity—>Locus of Control	0.18	2.455	0.014	Supported
H1c: Epistemic curiosity—>Perceived functional benefit	0.258	4.191	0	Supported
H1d: Epistemic curiosity—>Perceived learner value	0.277	3.8	0	Supported
H2a: Security Risk—>Computer Self-Efficacy	0.254	3.4	0.001	Supported
H2b: Security Risk—>Locus of Control	0.236	3.453	0.001	Supported
H2c: Security Risk—>Perceived functional benefit	0.092	1.559	0.12	Not supported
H2d: Security Risk—>Perceived learner value	-0.065	0.898	0.37	Not supported
H3a: Social Influence—>Computer Self-Efficacy	0.138	1.967	0.05	Supported
H3b: Social Influence—>Locus of Control	0.291	4.442	0	Supported
H3c: Social Influence—>Perceived functional benefit	0.271	4.728	0	Supported
H3d: Social Influence—>Perceived learner value	0.204	3.323	0.001	Supported
H4a: Computer Self-Efficacy—>Perceived functional benefit	0.091	1.394	0.164	Not supported
H4b: Computer Self-Efficacy—>Perceived learner value	0.21	2.487	0.013	Supported
H5a: Locus of Control—>Perceived functional benefit	0.231	3.288	0.001	Supported
H5b: Locus of Control—>Perceived learner value	0.189	2.785	0.006	Supported
H6: Perceived functional benefit—>Mobile Learning adoption	0.36	4.725	0	Supported
H7: Perceived learner value—>Mobile Learning adoption	0.432	5.419	0	Supported

Table 5 Hypothesis testing for Mobile learning adoption model (indirect effect)

	Original sample (O)	T statistics (|O/STDEV|)	*P* Values	Bias	2.50%	97.50%
Epistemic curiosity—>Locus of Control—>Perceived functional benefit	0.042	2.23	0.026	− 0.002	0.013	0.088
Security Risk—>Locus of Control—>Perceived functional benefit	0.055	2.498	0.013	− 0.002	0.026	0.111
Social Influence—>Locus of Control—>Perceived functional benefit	0.067	2.577	0.010	− 0.002	0.03	0.135
Social Influence—>Locus of Control—>Perceived learner value	0.055	2.501	0.013	− 0.002	0.018	0.105
Computer Self-Efficacy—>Perceived learner value—>Mobile Learning adoption	0.091	2.128	0.034	0.003	0.024	0.186
Locus of Control—>Perceived learner value—>Mobile Learning adoption	0.082	2.453	0.015	− 0.002	0.028	0.156
Locus of Control—>Perceived functional benefit—>Mobile Learning adoption	0.083	2.761	0.006	− 0.001	0.039	0.159
Security Risk—>Locus of Control—>Perceived functional benefit—>Mobile Learning adoption	0.02	2.112	0.035	− 0.001	0.008	0.05
Social Influence—>Locus of Control—>Perceived functional benefit—>Mobile Learning adoption	0.024	2.557	0.011	− 0.001	0.011	0.05
Social Influence—>Locus of Control—>Perceived learner value—>Mobile Learning adoption	0.024	2.105	0.036	− 0.001	0.008	0.057

When testing the hypothesis, as shown in Table 4, it was observed that epistemological factors significantly affected computer self-efficacy, locus of control, perceived functional benefit, and perceived learner value (H1a, H1b, H1c, and H1d all were supported). Security risk did not affect perceived functional benefit, and perceived learner value directly (H2c and H2d not supported) but affected computer self-efficacy and locus of control (H2a and H2b supported). Social factors affected computer self-efficacy, locus of control, perceived functional benefit, and perceived learner value (H3a, H3b, H3c, and H3d all supported).

Computer self-efficacy showed a significant effect on perceived learner value but not on perceived functional benefit (H4a unsupported but H4b supported) whereas locus of control showed a relation with both perceived functional benefit, and perceived learner value (H5a and H5b both supported). Finally, both perceived functional benefit and perceived learner value impacted mobile learning adoption (H6 and H7 were supported).

The mediation effect can be tested in the model for an indirect effect, as suggested by (Preacher & Hayes, 2004; Shrout & Bolger, 2002). The mediation effect came out to be significant for the indirect effect, as shown in Table 5. Locus of control mediated the relationship between epistemological curiosity, security risk, social influence, and perceived functional benefit with a p-value of 0.026, 0.013, $0.010 < 0.05$ (95% sig level) and between social influence and perceived learner value as p-value $0.013 < 0.05$ (95% sig level).

It was also found that perceived learner value mediated the relationship between self-efficacy and locus of control and mobile learning continuance as p-value

0.034 < 0.05 and 0.015 < 0.05(95% sig level). The perceived functional benefit mediated between locus of control and mobile learning continuance as *p*-values observed was 0.006 < 0.10 (95% sig value). For all these values, zero did not fall between upper-level and lower-level confidence intervals and hence the indirect effect was confirmed by bootstrapping.

Discussion

When answering the two research questions raised at the beginning of the research.e. RQ1: Do epistemological, social, and security risk factors affect perceived functional benefits (PFB) and perceived learner value (PLV)? It was found that H1(a, b, c, and d), H2(a and b), and H3(a, b, c, and d) all were supported. While answering the second research question i.e. RQ2: Does locus of control and computer self-efficacy mediate the relationship between epistemological, social, and security risk factors and perceived functional benefits (PFB) and perceived learner value (PLV)? The findings showed that computer self-efficacy was only related to PLV (H4b supported) while locus of control was related to PFB and PLV and H5(a and b) both supported. It was found that locus of control mediated between epistemological, social, and security risk factors affect perceived functional benefits.

Theoretical contribution

Current research has found epistemological and social factors along with security risks to be antecedents of mobile learning. The previous study by Magsayo (2023) found only security risk to be a significant predictor in mobile learning acceptance continuance and dropped epistemological and social factors. This led to exploring epistemological and social factors as the antecedent of mobile learning along with security risk and tested their relationship to perceived functional benefit and perceived learner value. The study elaborated on the work of Magsayo (2023) and added computer self-efficacy along with internal locus of control as personality traits and perceived functional benefit and perceived learner value to understand mobile acceptance continuance.

First, the three factors epistemological, social, and security risk all were tested for their effect on computer self-efficacy and locus of control. It was found that epistemological factors affected computer self-efficacy and locus of control and both the perceived functional benefit and perceived learner value. Epistemological curiosity reflects how the learner wants to learn by exploring new concepts and showing a high level of curiosity during the learning process. Learning on the mobile platform can help them satisfy their need for curiosity for new ideas and gain knowledge and concepts (Abdullah et al., 2017; Olufadi, 2015).

Security risk affected computer self-efficacy and locus of control but did not affect perceived functional benefit and perceived learner value directly. A learner may feel more confident and have a higher locus of control if he/she feels that during mobile learning there is no threat to his data privacy and security and his perceived security is high. Previous research has shown a direct relationship between security risk and the use of M-learning (Al-Adwan et al, 2018; Almaiah et al., 2020; Hamidi & Chvosshi, 2018) or an indirect effect (Nikou & Economides, 2017; Obiria & Kimwele, 2017).

Social factors affected computer self-efficacy and locus of control and again both perceived functional benefit, and perceived learner value. Social influence play's an important role in learning and during mobile learning individuals when connecting to the right peers may find improved self-efficacy and locus of control leading to a higher level of perceived benefits and overall learning value. This confirms previous work that perceived social influence does affect M-learning adoption because peer acceptance leads to greater popularity and higher status symbol (Pramana, 2018; Sanchez-Prieto et al., 2019; Yeap et al., 2016; Shukla, 2021; Sidik & Syafar, 2020).

Finally, the mobile learning continuance could be explained by perceived functional benefit and perceived learner value. So, when the learner feels that they are receiving function benefit from mobile learning, they want to continue learning through this mode. The functional benefit could be ease of use or flexibility. Learners also look out for the learning value they gain for learning.

The mediation showed that the locus of control mediated the relationship between epistemological curiosity, security risk, social influence, and perceived functional benefit and between social influence and perceived learner value. All three aspects of mobile learning i.e., epistemological curiosity, security risk, and social influence effects perceived functional benefit through the locus of control, and the locus of control is also mediating the relationship between social influence and perceived learner value. Hence, locus of control is one aspect of the learner that helps in building a higher perception regarding functional benefits and learner value for the intention to adopt mobile learning. Perceived learner value mediated the relationship between self-efficacy and locus of control and mobile learning continuance and perceived functional benefit mediated between locus of control and mobile learning continuance.

Managerial implications

The managerial implications can be many firstly the study provides a direction as to what the learner is looking for when learning through mobile learning, which has picked up during the COVID times. Learners are interested in learning new ideas and concepts and looking for more creative ways to satisfy their curiosity. They are looking out for a more secure platform where their personal information is safeguarded, and they can maintain confidentiality at their own pace and grades. They are also looking for more collaborative learning through mobile learning where they can connect with peers and friends who are interested in the same topics. This led us to understand the needs of learners when designing any content for M-learning.

Secondly, it is quite visible that the intention to continue learning on M-learning is impacted by two important criteria like perceived learner value and perceived functional benefit. Perceived functional benefit talks about useful learning through M-Learning like flexibility and pace are achieved and perceived learner value is the overall value gained by learning through M-learning. The biggest advantage of M-Learning is the ease and mobility achieved while learning as you can even look at the content while traveling.

Slowly with the emerging technology learner are looking out for avenues in which learning is not restricted to place or location and due to time constraints, they may view the contents at any time and submit their assignment while on the move. M-learning has broken all boundaries of learning and given extreme flexibility to the learner, which is the need of the day.

Limitations and future scope

The study was more focused on looking at the relationship between various aspects of Mobile learning and creating new hypotheses and building theory by testing the proposed conceptual model. Hence, the study took a small sample and used SAMRT PLS to create an SEM model. The future study can take a larger sample and confirm the proposed model. The same model can be tested in different cultural contexts to see its generalizability and look at specific factors suitable for each culture.

The study considered only three aspects of M-learning epistemological, social, and security risk, but future studies can look into other factors, which could be relevant for generating perceived functional benefit and learner value in the context of M-learning. More in-depth studies can be undertaken to understand the sub-dimension of epistemological curiosity and how the content developed for M-learning can help satisfy the creativity of learners.

Conclusion

Mobile learning is catching up fast due to time constraints and the amount of flexibility needed by the learner. Many countries including India have improved their connectivity and availability of Wi-Fi on mobiles. Individuals prefer to use their mobile phones for all their day-to-day activities like online payment and shopping. The use and acceptability of mobile phones have gone to the grassroots in India. Learning through mobile can be one great way to impart learning to all socio-economic levels in society and spread learning in a faster yet more acceptable way.

Acknowledgements
Not applicable.

Author contributions
Both the authors have contributed equally.

Funding
No funding was used for this research.

Availability of data and materials
The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 28 April 2023 Accepted: 1 July 2023
Published online: 10 July 2023

References

Abdullah, M. A., Ebiary, Y. B., & Al-Sammarraie, N. (2017). Determine factors influencing mobile learning acceptance in higher education institution of Malaysia: Online based learning. *International Journal on Contemporary Computer Research, 1*(1), 43–49.

Al-Adwan, A. S., Al-Madadha, A., & Zvirzdinaite, Z. (2018). Modeling students' readiness to adopt mobile learning in higher education: An empirical study. *The International Review of Research in Open and Distributed Learning*. https://doi.org/10.19173/irrodl.v19i1.3256

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. M. (2020). Analysis the effect of different factors on the development of mobile learning applications at different stages of usage. *IEEE Access: Practical Innovations, Open Solutions, 8*, 16139–16154. https://doi.org/10.1109/access.2019.2963333

Bagozzi, R., University of Michigan. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems, 8*(4), 244–254. https://doi.org/10.17705/1jais.00122

Bandura, A., Adams, N. E., & Beyer, J. (1977). Cognitive processes mediating behavioral change. *Journal of Personality and Social Psychology, 35*(3), 125–139.

Bandura, A. (1985). *Social foundations of thought and action: A social cognitive theory*. Pearson.

Barling, J., & Beattie, R. (1983). Self-efficacy beliefs and sales performance. *Journal of Organizational Behavior Management, 5*(1), 41–51.

Bashir, S., Khwaja, M. G., Rashid, Y., Turi, J. A., & Waheed, T. (2020). Green brand benefits and brand outcomes: The mediating role of green brand image. *SAGE Open, 10*(3), 2158244020953156.

Bere, A., & Rambe, P. (2016). An empirical analysis of the determinants of mobile instant messaging appropriation in university learning. *Journal of Computing in Higher Education, 28*(2), 172–198.

Berlyne, D. E. (1954). A theory of human curiosity. *British Journal of Psychology, 45*(3), 256.

Böhm, S., & Constantine, G. P. (2016). Impact of contextuality on mobile learning acceptance: An empirical study based on a language learning app. *Interactive Technology and Smart Education, 13*(2), 107–122.

Bojórquez, M., Vergara Villegas, E., Sanchez, C., García-Alcaraz, V. G., & Vara, J. L. (2016). Study on mobile augmented reality adoption for Mayo language learning. *Mobile Information Systems*.

Briz-Ponce, L., Pereira, A., Carvalho, L., Juanes-Méndez, J. A., & García-Peñalvo, F. J. (2017). Learningwith mobile technologies-students. *Computers in Human Behavior, 72*, 612–620.

Camilleri, M. A., & Camilleri, A. C. (2019). The students' readiness to engage with mobile learning apps. *Interactive Technology and Smart Education, 17*, 28–38.

CHED. (2020). CHED COVID-19 ADVISORY NO. 3. Retrieved from https://ched.gov.ph/wp-content/uploads/CHED-COVID-2019-Advisory-No.-3.pdf

Cheng, Y. M. (2015). Towards an understanding of the factors affecting m-learning acceptance: Roles of technological characteristics and compatibility. *Asia Pacific Management Review*, *20*(3), 109–119.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189–211.

Crompton, H. (2022). Support provided for K-12 teachers teaching remotely with technology during emergencies: A systematic review. *Journal of Research on Technology in Education, 54*(3), 473–489. https://doi.org/10.1080/15391523.2021.1899877

Crompton, H., & Burke, D. (2018). The use of mobile learning in higher education: A systematic review. *Computers & Education, 123*, 53–64.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

Deci, E. L. (1975). Intrinsic motivation. *New York and London. Plenum Press, 10*, 978–971.

Deng, X., Doll, W., & Truong, D. (2004). Computer self-efficacy in an ongoing use context. *Behaviour & Information Technology, 23*(6), 395–412. https://doi.org/10.1080/01449290410001723454

Fagan, M. H. (2019). Factors influencing student acceptance of mobile learning in higher education. *Computers in the Schools: Interdisciplinary Journal of Practice, Theory, and Applied Research, 36*(2), 105–121. https://doi.org/10.1080/07380569.2019.1603051

Fassott, G., Henseler, J., & Coelho, P. S. (2016). Testing moderating effects in PLS path models with composite variables. *Industrial Management + Data Systems, 116*(9), 1887–1900. https://doi.org/10.1108/imds-06-2016-0248

Fatima, J. K., Ghandforoush, P., Khan, M., & Mascio, R. D. (2019). Mobile learning adoption for tourism education in a developing country. *Current Issues in Tourism, 22*(4), 420–427. https://doi.org/10.1080/13683500.2018.1434135

Gallarza, M. G., Arteaga, F., Del Chiappa, G., Gil-Saura, I., & Holbrook, M. B. (2017). A multidimensional service-value scale based on Holbrook's typology of customer value: Bridging the gap between the concept and its measurement. *Journal of Service Management, 28*(4), 724–762. https://doi.org/10.1108/josm-06-2016-0166

Gong, M., Xu, Y., & Yu, Y. (2004). An enhanced technology acceptance model for web-based learning. *Journal of Information Systems Education*, 15(4).

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). Advanced issues in partial least squares structural equation modeling.

Hair, J., Hult, G., Ringle, C., & Sarstedt, M. (2014). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage Publications.

Hamidi, H., & Chavoshi, A. (2018). Analysis of the essential factors for the adoption of mobile learning in higher education: A case study of students of the University of Technology. *Telematics and Informatics, 35*(4), 1053–1070. https://doi.org/10.1016/j.tele.2017.09.016

Hao, S., Dennen, V. P., & Mei, L. (2017). Influential factors for mobile learning acceptance among Chinese users. *Educational Technology Research and Development: ETR & D, 65*(1), 101–123. https://doi.org/10.1007/s11423-016-9465-2

Hashim, K. F., Tan, F. B., & Rashid, A. (2015). Adult learners' intention to adopt mobile learning: A motivational perspective: Adult learners' intention to adopt mobile learning. *British Journal of Educational Technology: Journal of the Council for Educational Technology, 46*(2), 381–390. https://doi.org/10.1111/bjet.12148

Hassan, W. U., Nawaz, M. T., Syed, T. H., Arfeen, M. I., Naseem, A., & Noor, S. (2015). *Investigating Students' Behavioral Intention Towards Adoption of Mobile Learning in Higher Education Institutions of Pakistan* (p. 20). University of Engineering and Technology Taxila.

Hayashi, A. (2004). The role of social presence and moderating role of computer self efficacy in predicting the continuance usage of e-learning systems. *Journal of Information Systems Education, 20*(3), 139–154.

Hsia, J. W. (2016). The effects of locus of control on university students' mobile learning adoption. *Journal of Computing in Higher Education*, *28*, 1–17.

Hsia, J.-W., Chang, C.-C., & Tseng, A.-H. (2014). Effects of individuals' locus of control and computer self-efficacy on their e-learning acceptance in high-tech companies. *Behaviour & Information Technology, 33*(1), 51–64. https://doi.org/10.1080/0144929x.2012.702284
Hu, P.J.-H., Clark, T. H. K., & Ma, W. W. (2003). Examining technology acceptance by school teachers: A longitudinal study. *Information & Management, 41*(2), 227–241. https://doi.org/10.1016/s0378-7206(03)00050-8
Hwang, G.-J., & Fu, Q.-K. (2019). Trends in the research design and application of mobile language learning: A review of 2007–2016 publications in selected SSCI journals. *Interactive Learning Environments, 27*(4), 567–581. https://doi.org/10.1080/10494820.2018.1486861
Hwang, G. J., & Tsai, C. C. (2011). Research trends in mobile and ubiquitous learning: A review of publications in selected journals from 2001 to 2010. *British Journal of Educational Technology, 42*(4), E65–E70.
Iqbal, S., & Bhatti, Z. A. (2017). What drives m-learning? An empirical investigation of university student perceptions in Pakistan. *Higher Education Research & Development, 36*(4), 730–746. https://doi.org/10.1080/07294360.2016.1236782
Jia, H. M., Wang, Y., Ge, L., Shi, G., & Yao, S. (2012). Asymmetric effects of regulatory focus on expected desirability and feasibility of embracing self-service technologies: Jia, Wang, Ge, Shi, and Yao. *Psychology & Marketing, 29*(4), 209–225. https://doi.org/10.1002/mar.20516
Karimi, S. (2016). Do learners' characteristics matter? An exploration of mobile-learning adoption in self-directed learning. *Computers in Human Behavior, 63*, 769–776. https://doi.org/10.1016/j.chb.2016.06.014
Kelman, H. C. (1958). Compliance, identification, and internalization three processes of attitude change. *The Journal of Conflict Resolution, 2*(1), 51–60. https://doi.org/10.1177/002200275800200106
Kim, H.-J., Lee, J.-M., & Rha, J.-Y. (2017). Understanding the role of user resistance on mobile learning usage among university students. *Computers & Education, 113*, 108–118. https://doi.org/10.1016/j.compedu.2017.05.015
Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration (Ijec), 11*(4), 1–10.
Koo, D.-M. (2009). The moderating role of locus of control on the links between experiential motives and intention to play online games. *Computers in Human Behavior, 25*(2), 466–474. https://doi.org/10.1016/j.chb.2008.10.010
Kumar, J. A., & Bervell, B. (2019). Google Classroom for mobile learning in higher education: Modelling the initial perceptions of students. *Education and Information Technologies, 24*(2), 1793–1817. https://doi.org/10.1007/s10639-018-09858-z
Leong, L. W., Ibrahim, O., Dalvi-Esfahani, M., Shahbazi, H., & Nilashi, M. (2018). The moderating effect of experience on the intention to adopt mobile social network sites for pedagogical purposes: An extension of the technology acceptance model. *Education and Information Technologies, 23*(6), 2477–2498. https://doi.org/10.1007/s10639-018-9726-2
Lefcourt, H. M. (1982). *Locus of control: Current trends in theory and research* (2nd ed.). Erlbaum.
Litman, J. A., & Spielberger, C. D. (2003). Measuring epistemic curiosity and its diversive and specific components. *Journal of Personality Assessment, 80*(1), 75–86. https://doi.org/10.1207/S15327752JPA8001_16
Liu, Y., Li, H., & Carlsson, C. (2010). Factors driving the adoption of m-learning: An empirical study. *Computers & Education*, *55*(3), 1211–1219.
Luttrell, V. R., & Richard, D. C. S. (2011). Development of the higher education value inventory: Factor structure and score reliability. *Psychology, 2*(09), 909–916. https://doi.org/10.4236/psych.2011.29137
Magsayo, R. T. (2023). Mobile learning adoption continuance: Role of locus of control on its determinants. *Interactive Technology and Smart Education, 20*(2), 177–208.
Masrek, M., & Samadi, I. (2017). Determinants of mobile learning adoption in higher education setting. *Asian Journal of Scientific Research, 10*(2), 60–69.
Milošević, I., Živković, D., Manasijević, D., & Nikolić, D. (2015). The effects of the intended behavior of students in the use of M-learning. *Computers in Human Behavior, 51*, 207–215. https://doi.org/10.1016/j.chb.2015.04.041
Mittal, N., & Alavi, S. (2020). Construction and psychometric analysis of teachers mobile learning acceptance questionnaire. *Interactive Technology and Smart Education, 17*(2), 171–196. https://doi.org/10.1108/itse-07-2019-0039
Nikou, S. A., & Economides, A. A. (2017). Mobile-based assessment: Investigating the factors that influence behavioral intention to use. *Computers & Education, 109*, 56–73. https://doi.org/10.1016/j.compedu.2017.02.005
Obiria, P. B., & Kimwele, M. W. (2017). A location-based privacy-preserving m-learning model to enhance distance education in Kenya. *Journal of Computers in Education, 4*(2), 147–169. https://doi.org/10.1007/s40692-017-0079-4
Olufadi, Y. (2015). Gravitating towards mobile phone (GoToMP) during lecture periods by students: Why are they using it? and how can it be measured? *Computers & Education, 87*, 423–436. https://doi.org/10.1016/j.compedu.2015.08.013
Ong, C.-S., & Lai, J.-Y. (2006). Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Computers in Human Behavior, 22*(5), 816–829. https://doi.org/10.1016/j.chb.2004.03.006
Padilla-Meléndez, A., Garrido-Moreno, A., Del Aguila-Obra, A. R., Park, S. Y., Nam, M. W., & Cha, S. B. (2008). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British Journal of Educational Technology, 51*(2), 592–605.
Park, S. Y., Nam, M.-W., & Cha, S.-B. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model: Factors related to use mobile learning. *British Journal of Educational Technology: Journal of the Council for Educational Technology, 43*(4), 592–605. https://doi.org/10.1111/j.1467-8535.2011.01229.x
Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *The Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
Poong, Y. S., Yamaguchi, S., & Takada, J.-I. (2017). Investigating the drivers of mobile learning acceptance among young adults in the World Heritage town of Luang Prabang. *Laos. Information Development, 33*(1), 57–71. https://doi.org/10.1177/0266666916638136
Pramana, E. (2018). Determinants of the adoption of mobile learning systems among university students in Indonesia. *Journal of Information Technology Education Research, 17*, 365–398. https://doi.org/10.28945/4119
Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*, *36*, 717–731.

Qashou, A. (2021). Influencing factors in M-learning adoption in higher education. *Education and Information Technologies, 26*(2), 1755–1785. https://doi.org/10.1007/s10639-020-10323-z
Roca, J. C., Chiu, C.-M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. *International Journal of Human-Computer Studies, 64*(8), 683–696. https://doi.org/10.1016/j.ijhcs.2006.01.003
Sabah, N. M. (2016). Exploring students' awareness and perceptions: Influencing factors and individual differences driving m-learning adoption. *Computers in Human Behavior, 65*, 522–533. https://doi.org/10.1016/j.chb.2016.09.009
Sánchez-Prieto, J. C., Hernández-García, Á., García-Peñalvo, F. J., Chaparro-Peláez, J., & Olmos-Migueláñez, S. (2019). Break the walls! Second-Order barriers and the acceptance of mLearning by first-year pre-service teachers. *Computers in Human Behavior, 95*, 158–167. https://doi.org/10.1016/j.chb.2019.01.019
Saroia, A. I., & Gao, S. (2019). Investigating university students' intention to use mobile learning management systems in Sweden. *Innovations in Education and Teaching International, 56*(5), 569–580. https://doi.org/10.1080/14703297.2018.1557068
Shorfuzzaman, M., Hossain, M. S., Nazir, A., Muhammad, G., & Alamri, A. (2019). Harnessing the power of big data analytics in the cloud to support learning analytics in mobile learning environment. *Computers in Human Behavior, 92*, 578–588. https://doi.org/10.1016/j.chb.2018.07.002
Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological methods*, *7*(4), 422.
Shukla, S. (2021). M-learning adoption of management students': A case of India. *Education and Information Technologies, 26*(1), 279–310. https://doi.org/10.1007/s10639-020-10271-8
Sidik, D., & Syafar, F. (2020). Exploring the factors influencing student's intention to use mobile learning in Indonesia higher education. *Education and Information Technologies, 25*(6), 4781–4796. https://doi.org/10.1007/s10639-019-10018-0
Spector, P. E. (1982). Behavior in organizations as a function of employee's locus of control. *Psychological Bulletin, 91*(3), 482.
Terzis, V., & Economides, A. A. (2011). The acceptance and use of computer based assessment. *Computers & Education, 56*(4), 1032–1044. https://doi.org/10.1016/j.compedu.2010.11.017
Thongsri, N., Shen, L., Bao, Y., & Alharbi, I. M. (2018). Integrating UTAUT and UGT to explain behavioural intention to use M-learning". *Journal of Systems and Information Technology, 20*(3), 278–297.
Thongsri, N., Shen, L., & Bao, Y. (2019). Investigating factors affecting learner's perception toward online learning: Evidence from ClassStart application in Thailand. *Behaviour & Information Technology, 38*(12), 1243–1258. https://doi.org/10.1080/0144929x.2019.1581259
Tung, F.-C., & Chang, S.-C. (2008). A new hybrid model for exploring the adoption of online nursing courses. *Nurse Education Today, 28*(3), 293–300. https://doi.org/10.1016/j.nedt.2007.06.003
Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information Technology Theory and Application, 11*(2), 5–40.
Venkatesh, M., & Davis, D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems, 27*(3), 425. https://doi.org/10.2307/30036540
Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences, 27*(3), 451–481. https://doi.org/10.1111/j.1540-5915.1996.tb00860.x
Wang, Y.-S., Wu, M.-C., & Wang, H.-Y. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. *British Journal of Educational Technology: Journal of the Council for Educational Technology, 40*(1), 92–118. https://doi.org/10.1111/j.1467-8535.2007.00809.x
Watjatrakul, B. (2016). Online learning adoption: Effects of neuroticism, openness to experience, and perceived values. *Interactive Technology and Smart Education, 13*(3), 229–243. https://doi.org/10.1108/itse-06-2016-0017
Yeap, J. A. L., Ramayah, T., & Soto-Acosta, P. (2016). Factors propelling the adoption of m-learning among students in higher education. *Electronic Markets, 26*(4), 323–338. https://doi.org/10.1007/s12525-015-0214-x

Publisher's Note

Neerja Kashive is presently working as Associate Dean-Research at VES's Business School. She has completed her Ph.D. from Mumbai University in the area of employer branding with the title, "Impact of Employer and Employee branding on Organizational attractiveness and Firm performance in IT Sector in Mumbai". Her area of research focusses on employer branding, internal branding, E-learning, Artificial intelligence, gamification and technology in HR. She is certified in HR Analytics profession and conducts workshops & seminars.

Dharini Phanshikar is a student of PGDM-HR in VES Business School. She has her interest area in mobile learning, E-learning, HR technology and Artificial intelligence in HR. She has presented many research papers in this topic in different research conferences.