Learning technology acceptance and continuance intention among business students: The mediating effects of confirmation, flow, and engagement

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The emergence of mobile applications has opened the door to a new kind of information and communication technology tool and educational support which is vital for students' positive learning behaviours. The aims of this study were to examine the effects of three mediators (confirmation, flow, and student engagement) on students' learning technology acceptance and information systems continuance intention, and to explore the functions of these variables in the mediating process between learning technology acceptance and continuance intention. Using PROCESS macro program where the bootstrap confidence interval was adopted, a parallel multiple mediation model and a serial multiple mediation model were tested. Two of the three proposed hypotheses were supported. Business students' confirmation and flow, elicited by the m-learning app, were two mediating factors with high ratios (0.6655, 95% CI = 0.2635 to 0.6085) of the overall indirect effect to the total effect, which related to students' decisions in continuous usages of the technology. We concluded that the continuous use of the m-learning app was driven not only by students' flexible thinking skills in accepting new learning technology, but also by a set of cognitive attributes reflecting users' positive experiences with the system.

Implications for practice or policy:

- Business students who have positive mindsets for accepting new technology will try their best to overcome challenges of learning unfamiliar technologies.
- Business students' confirmation and flow experience elicited by the m-learning app aids in understanding of their intention to continue using the system.
- Instructors must develop partnerships with instructional designers to enhance student confirmation, flow and engagement for better acceptance and continued use of mobile learning technologies.

Keywords: mobile application in learning; learning technology acceptance; continuance intention; flow experience; higher education;

Introduction

Mobile technologies have been utilised as interactive and connective tools to facilitate students' learning engagement and have become prevalent in many disciplines in higher education. Mobile technologies and pedagogy can be embedded in a variety of learning tasks no matter how a course is delivered (face-to-face, hybrid, or online learning) or whether learning is taking place formally and informally. Mobile learning (m-learning) is defined as, "learning across multiple contexts, through social and content interactions, using personal electronic devices" (Crompton, 2013, p. 4). It can effectively increase students' collaboration skills (Alioon & Delialioğlu, 2019; Hamidi & Chavoshi, 2018), engage students in higher-order thinking (Hwang et al., 2018), and positively impact students' high-level cognitive skills (Saedi et al., 2018). Most importantly, the emergence of mobile applications (apps) has opened the door to a new kind of information and communication technology (ICT) tool and educational support which is vital for students' positive learning behaviours (i.e., motivation, learning community, engagement, and collaboration). Notari et al. (2016) classified educational apps as having two main focuses. The first focus is on instructional design criteria which address the learning goals of a given app. The functionalities of these apps emphasise transmitting information, facilitating communication, or collaboration, fostering situated learning. The second focus is on motivational domains in learning. These apps apply strategies such as gamification, reward systems, or the amount of infotainment used to motivate learners in enjoyable learning situations. Both classifications of educational apps have been widely utilised for students' learning resulting in technology integrations promoting students' interest in learning and engagement.

m-learning acceptance can contribute to students' success, however, the factors that affect the use and user acceptance of m-learning are still controversial (Almaiah & Al Mulhem, 2019). Technology utilisations in the classroom or in an online/hybrid learning environment may not have the same effects on all students. Some students might feel motivated and engaged, while others could lose interest in, or attraction to, learning when electronic devices are readily available in their learning process. This is because individuals have different levels of ability to adapt the cognitive processing strategies when they face new and unexpected conditions (i.e., new learning situations or new digital technologies that instructors were adapting in teaching) in the environment (Cañas et al., 2003; Tseng & Hill, 2020). This skill is called cognitive flexibility. This adaption is not always successful since technology could become more of a burden than an aid and be a distracting factor in a student's attention and engagement. Alexopoulou et al. (2020) argued that since learning processes themselves are always evolving and constantly reconfigured, it is vital for students to be more flexible and open-minded to adapting new technologies. In addition, Barak and Levenberg (2016a, 2016b) concluded that one of the important skills for twenty-first century learners is learning technology acceptance and adaption. They also stressed that learning technology acceptance (LTA) is one of the key antecedents of effective learning in technology-enhanced environments. This is extensively studied in explaining and predicting user behaviour in information systems (IS) acceptance and continuance (Al-Emran et al., 2020; Joo et al., 2018; Ye et al., 2019).

Several studies have pointed out the importance of understanding educators and learners' adoption of m-learning technologies and the human-computer interactions. Learners' behaviours, such as confirmation (Hossain et al., 2020) and flow experience (Chang et al., 2016; Hamidi & Chavoshi, 2018) have been concluded as essential factors for learners to make a continuance decision in accepting or rejecting a variety of technologies (Dalvi-Esfahani et al., 2020). Chang (2013) defined continuance intention of using technology as the degree to which an individual is willing to use systems in the future and to recommend them to others (e.g., friends). More specifically, Lin (2012) defined the continuance intention of using IS as "the continued usage of IS by adopters, where a continuance decision follows an initial acceptance decision" (p. 500). However, other research findings indicated that there was a lack of literature examining user IS continuance focusing on mobile apps in learning (Nabavi et al., 2016).

Literature review

Gap in the literature

There is a gap in the m-learning literature, reflecting a lack of investigation of students' flow experience and IS continuance intention while using educational mobile apps. A thorough literature review of IS continuance intention articles was conducted by Nabavi et al. (2016), who reviewed 191 studies carried out from 2001 and 2014 and published in 64 different journals. They analysed the literature based on a series of dimensions including year of publication, journal, author, the theories and theorical constructs utilised, and the contexts and technologies examined. Their findings suggested IS continuance intention would become an emerging academic research topic. In terms of the contexts and technologies examined, a total of 39 studies focused on mobile technology. Specifically, most of them were related to the use of mobile internet service (n = 11), followed by mobile data service (n = 6), mobile commerce (n = 4), and mobile banking (n = 3). Only one study focused on studying users' digital learning and IS continuance intention from mobile application (Chen et al., 2012).

The first time the term *confirmation* is included in a theoretical model as a conceptual variable is in Bhattacherjee's (2001) expectation-confirmation model referring to IS continuous use. The expectation-confirmation model posits that intention to continue IS usage can be explained by three variables: confirmation, perceived usefulness, and satisfaction. He referred to confirmation as users' perception of the congruence between expectation of IS use and its actual performance. This construct has been utilised extensively in consumer behaviour studies. Later, Bhattacherjee and Premkumar (2004) used the term *disconfirmation* to capture the discrepancies between users' original expectation and observed performance. According to Bhattacherjee's (2001) explanations, positive confirmation emerges when performance exceeds expectation, and vice versa. In this study, we adopted the confirmation label to examine business students' realisation of the expected benefits of the mobile app used. This is referred to as a business students' perception of the congruence between their original expectation and the actual performance pertaining to an educational mobile app. However, according to a review of literature, only a few studies focused on investigating the direct association between confirmation and users' IS continuance intention

(Dai et al., 2020; Li et al., 2019), and none are in the context of using digital apps for m-learning. For instance, Li et al. (2019) investigated 211 users' intention to continue using social fitness-tracking apps, and their findings suggested that confirmation has significant and positive effects ($p < 0.001$) on individuals' continuous intention of using fitness-tracking apps.

The theory of flow experience (Csikszentmihalyi, 1990; Csikszentmihalyi & Csikszentmihalyi, 1988) has been applied as the core framework of most fundamental studies to better understand and investigate students' attention and perceived enjoyment in an interactive learning situation (e.g., Guo et al., 2016; Hamari et al., 2016). When learners are so involved in and enjoying an activity that they do not hesitate to face challenges, they are experiencing the state of flow. In the extant literature, flow experience is used to address optimal user behaviours and experiences in human-computer interaction. Research findings have indicated the significant effects of flow experience on IS continuance intention (Liu et al., 2018; Yang & Lee, 2018). In business and marketing, researchers place more of an emphasis on the investigation of the effect of consumer's experience of using company website (or social networking site) on continuance usage intention (Zhou & Liu, 2014) and brand loyalty (Kaur et al., 2016; Ruiz-Mafe et al., 2014). As in educational research most of the literature utilised flow experience to ascertain learners' involvement and engagement with information learning system (Cheng, 2020; Khan et al., 2017), online learning (Guo et al., 2016), and game-based learning (Chang et al., 2016; Huang et al., 2015). However, there does seem to be a lack of evidence in the literature which studied students' flow experience when utilising mobile apps in their learning process.

In addition, studies have indicated that m-learning technology can promote learning engagement (Kim et al., 2020). Moreover, engagement was confirmed in Tsai et al.'s (2018) study as one of the types of interest in learning that led individuals to concentrate on active learning, which in turn, had positive effect to their continuance intention to use a MOOC system ($\beta = 0.407$, $t = 4.241$).

Aims of the study

While the direct relationships between learning technology acceptance, confirmation, flow experience, student engagement, and continuance intention were thoroughly explored in prior research efforts across multiple contexts (e.g., Al-Maroof & Salloum, 2021; Cheng, 2020; Liu et al., 2018; Tseng et al., 2020), the mechanism between the relationship of learning technology acceptance and continuance intention is still not clear, especially the functions through confirmation, flow experience, and student engagement with a focus on m-learning apps. This area needs exploration to unravel and see how these variables work together to help learning technology acceptance increase continuance intention. Hence, we argue that the development of a multiple mediation model is crucial, and there is a need to further examine the magnitude and significance of the causal connections between learning technology acceptance and continuance intention. The aims of this study were to develop and test a model that considered confirmation, flow, and engagement as three mediators that enhance the effects of learning technology acceptance on information systems continuance intention in business students. Accordingly, the research questions that guided the investigation were:

1. What is the mechanism between mobile learning app acceptance and continuance intention?
2. Among the mediators that link m-learning acceptance and continuance intention, which ones play a key role?
3. Do these mediators work in parallel with each other or serially?

A variety of mediation analysis techniques, such as structural equation modeling and the Baron and Kenny (1986) method, were used to examine mediated effects and relationships between learning technology acceptance and continuance intention in prior research. However, this study was the first test of a three-serial-mediator model for learning technology acceptance and continuance intention using Hayes' (2013) PROCESS macro program (based on principles of ordinary least squares regression) where the bootstrap confidence interval was adopted to test an indirect effect. Hayes (2013) considered the bootstrapping approach as the most powerful way in assessing indirect effects as well as the method least vulnerable to Type I errors.

Theoretical framework

Cognitive flexibility theory

We adopted the cognitive flexibility theory as the foundation of to develop our hypotheses. . Cognitive flexibility has been recognised as a key antecedent behaviour for adapting to new and unexpected environmental conditions (Cañas et al., 2003; Cohen et al., 2007). Mobile devices make real-time learning possible by involving learners in instant interactions with real contexts (Chen & Huang, 2012), facilitating two-way communication channels, and providing instant evaluation results with reinforced feedback. As those functionalities are utilised and embedded in a digital and ubiquitous learning context, cognition is established in the interaction and learning process. Learners in the twenty-first century face the rapid evolution of ICTs and participate in complex and unstructured tasks. According to Spiro and Jehng (1990), cognitive flexibility is "the ability to adaptively re-assemble diverse elements of knowledge to fit the particular needs of a given understanding or problem-solving situation" (p. 169). Concerning cognitive flexibility in learning processes in ICT's, within integration environments and from an educational perspective, Barak and Levenberg (2016a) proposed the flexible thinking in learning model and further developed the flexible thinking in learning scale (Barak & Levenberg, 2016b) which encompasses three higher-order thinking skills that are necessary for solving problems and structuring new knowledge. These three essential factors and skills are: (1) accepting new or changing technologies, (2) open-mindedness to others' ideas, and (3) adapting to changes in learning situations. These three factors were developed into three subscales in Barak & Levenberg (2016b). In this study, the researchers only used one subscale, as our independent variable, since it was the only subscale relevant to the research scope. The selected subscale, accepting new or changing technologies, referred to the ability to adjust to advanced technologies and effectively use them for meaningful learning (Barak & Levenberg, 2016a, 2016b).

Expectation-confirmation theory

Bhattacherjee (2001) proposed the expectation-confirmation model, which has gained attention and acceptance in investigating confirmation and IS continuance intention (Baker-Eveleth & Stone, 2015; Lin et al., 2015). Confirmation in the expectation-confirmation model refers to the users' subjective judgements when comparing their initial expectations with perceptions related to actual performance of a service/information system (Huang et al., 2019). A positive confirmation is reached when IS performs better than users expect otherwise, a negative confirmation is obtained. In ICT-rich learning environments, when users find their initial expectations are confirmed, they tend to elevate their perceived usefulness of the system. Moreover, they tend to have a higher level of motivation and are more likely to further explore the system's functionalities and become deeply involved in technology integration learning processes. Most importantly, according to Csikszentmihalyi (1975), experiencing a flow state is so enjoyable that individuals are eager to engage in the flow-generating activities again and expect to re-experience flow. Later, Liu et al. (2018) confirmed this concept in their study by examining users' flow experience in mobile games.

Hypotheses development

When students are more open to technological modifications, they are more likely to engage in learning, find the technology effective, and consequently make a continuance decision of accepting new technologies. Prior research has provided supportive evidence that technology acceptance can positively increase students' enjoyment in learning (Dawoud et al., 2015) and engagement (Barak, 2018; Tseng et al., 2020), which in turn, increases their willingness to continue using ICTs in the future. For example, findings from Tseng et al. (2020) indicated that learners with higher levels of technology acceptance were more engaged in their learning activities.

Confirmation and flow experience in the aspect of ICT

Previous studies on IS continuance have found significant effects of confirmation on flow experience (Cheng, 2020; Ifinedo, 2017; Lu et al., 2019), and indicated flow experience as an indirect mediator influencer of users' intention on the continued use of the system (Kang & Kim, 2018; Lin et al., 2020; Liu et al., 2018; Yang & Lee, 2018). For example, Cheng's (2020) study proposed a comprehensive structural model based on the Bhattacherjee's (2001) expectation-confirmation model and flow experience, and

investigated how those factors affected 368 medical professionals' continuance intention of the cloud-based e-learning system. The research findings suggested that medical professionals who indicated confirmation of expectations toward the cloud-based e-learning system were more likely to experience flow state by enjoying the system, and subsequently led to their continuance intention of future system usages.

Student engagement

When flow experience is utilised to explain IS users' behaviours from the aspect of intrinsic motivation (Zhou, 2012), engagement is defined as "a psychological state experienced because of focusing one's energy and attention on a coherent set of stimuli or meaningfully related activities and events" (Witmer & Singer, 1998, p. 227), and identified in literature as an essential component for students' learning accomplishment and success. According to Csikszentmihalyi (1975), if any activities or tasks are interesting but not too challenging to cause frustration or distraction, there is a likelihood for users to be engaged in the activities. Studies have found ICT-rich learning environments that invoke flow experience can increase the potential to affect consequent learning engagement (Al-Maroof & Salloum, 2021; Hamari et al., 2016; Lee, 2010). Moreover, m-learning products provide instant message exchanges, timely feedback functions, and facilitate interactions and collaborations, all of which may motivate learners in enjoyable learning situations and lead to concentration and engagement in learners (Anohah et al., 2017; Ryu & Parsons, 2012). All optimal learning experiences can increase students' self-confidence in seeking the next level of skills to meet new challenges, which in turn, can lead to higher intention to continuously use the m-learning system in learning.

From the above discussion of theoretical development and empirical evidence, the following hypotheses were proposed:

1. Confirmation mediates the relationship between learning technology acceptance and continuance intention.
2. Flow experience mediates the relationship between learning technology acceptance and continuance intention.
3. Student engagement mediates the relationship between learning technology acceptance and continuance intention.

Methodology

Course format

Two of the authors who taught graduate and undergraduate level business courses at the Jacksonville State University adopted the Top Hat app (https://tophat.com) in order to enhance the course experience by motivating students to learn, participate, and ultimately master course content. Features of the app utilised in the classroom included automatic attendance tracking, activity participation checking, course content posting, embedded in-class quizzes, and real-time feedback, in-class discussions, and polling, all accessible through the mobile app from a laptop, a cellphone, or other electronic devices such as an iPad. The purpose of adopting the mobile app by the instructors was to enhance student learning experience in the classroom, keeping students engaged in learning, and increase their attention and interest in the course materials while not taking their electronic devices away, and providing instant feedback on student learning outcomes.

Participants and instrumentation

Participants were graduate and undergraduate students enrolled in face-to-face courses in the business program at the Jacksonville State University in the United States. A total of 210 surveys were completed and returned. Of the participating students, 94 (44.5%) participants were female; and 116 (55.5%) participants were male (Table 1). The majority of participants (183, 87.1%) reported being in the 25 to 29 age range. More than 88% of participants indicated they had good or excellent internet skills.

Table 1
Demographic information of participants (N = 210)

Gender:	
Female	94 (44.5%)
Male	116 (55.5%)
Age:	
20-24	9 (4.3%)
25-29	183 (87.1%)
30-39	10 (4.8%)
40-49	2 (1.0%)
Over 50	5 (2.9%)
Internet skills:	
Poor	1 (0.5%)
Average	24 (11.4%)
Good	104 (49.5%)
Excellent	81 (38.6%)

The survey instrument (Appendix A) for this quantitative research took approximately 20 minutes to complete. In this study, students' learning technology acceptance was measured from one subscale of Barak and Levenberg's (2016b) flexible thinking in learning scale. It included five items, and measured using a 5-point Likert scale. The questions include, for example: "I adjust quickly to new learning technologies," and "I am open to update in new technological tools that can help me learn." Cronbach's alpha was used to examine this scale's reliability. A result of $\alpha = .872$ indicated a good degree of internal consistency.

For confirmation, a three item scale was adapted from Limayem et al. (2007). A sample item of this 7-point Likert scale was: "My overall experience with the Top Hat app was … (1 = *much worse than expected*; 7 = *much better than expected*)." The Cronbach's alpha of the scale in this study was .846, indicating good internal consistency.

For flow experience, a 5-point Likert scale was modified from Park et al. (2010) who developed survey questions based on Webster et al.'s (1993) categories. The results from 12 items grouped into four categories were: (a) control - 3 items; $\alpha = .658$, (b) attention focus - 3 items; $\alpha = .665$, (c) curiosity - 3 items; $\alpha = .921$, and (d) intrinsic interests - 3 items; $\alpha = .779$. All these Cronbach's alpha coefficients were acceptable and indicated good internal consistencies.

Scholars from more than 19 countries collaborated in the development of the student engagement in schools questionnaire (SESQ) (Lam & Jimerson, 2008) consisting of 12 items. The SESQ is a Likert-type, self-report questionnaire focused on the comprehensive assessment of the construct of student engagement. The Cronbach's alpha of the scale in this study was 0.929, indicating excellent internal consistency.

Continuance intention was measured by a three item, 5-point Likert scale modified from Thong et al. (2006). A sample item was: "I plan to continue using the Top Hat app if it is being utilized by the instructor in my next class." The Cronbach's alpha result of 0.953, showed excellent internal consistency had been achieved.

Data collection and statistical analysis

This study was approved by the Institutional Review Board at the Jacksonville State University at the beginning of the semester. During the last three weeks of the semester, a questionnaire containing the measures of learning technology acceptance, flow, confirmation, student engagement, and continuance intention was distributed in an online survey format. An access link to the survey was provided for students. The surveys took approximately 20 minutes to complete.

Common method bias is a potential threat to research findings when the data are collected from self-report responses for all variables. Thus, before the final data analysis, Harman's (1976) single factor test was used to assure there was no problem with common method bias in our data. Since the highest total variance extracted by one factor (35.08%) was less than the recommended threshold of 50%, it was suggested that common method bias did not affect the findings. Descriptive statistics and multivariate correlational analysis were conducted, and the results are shown in Table 2.

To test the hypotheses, Hayes' (2013) PROCESS macro models (based on principles of ordinary least squares regression where the bootstrap confidence intervals adopted) were utilised to assess whether there was a significant mediation effect. We computed 5,000 bootstrap bias-correlated 95% confidence intervals (BC CI) for mediation analyses as recommended by Hayes (2013) and Preacher and Hayes (2008).

Results

As shown in Table 2, all study variables were positively and significantly correlated with each other at the significance level of $p < .01$. Specifically, the Pearson correlation coefficients showed there were strong relationships between confirmation and flow ($r = 0.773$), confirmation and continuance intention ($r = 0.798$), and flow and continuance intention ($r = 0.769$).

Table 2
Descriptive statistics, reliability information of each scale, and Pearson coefficients between variables

Variable	LTA	Confirmation	Flow	Engagement	Continuance intention	Number of items	Cronbach α	*M*	*SD*
LTA	—	.344**	.292**	.386**	.399**	5	.872	4.13	.68
Confirmation †		—	.773**	.310**	.798**	3	.846	4.83	1.34
Flow			—	.313**	.769**	12	.831	3.06	.69
Student engagement				—	.302**	12	.929	4.03	.53
Continuance intention					—	3	.953	3.51	1.11

Note. $N = 210$, † 7-point Liker-type scale, ** $p < .01$; LTA, Learning technology acceptance

Examination of the mediation effects

First, we used the parallel multiple mediation model (3) of Hayes (2013) to examine whether learning technology acceptance would indirectly influence continuance intention through casually linked mediators of the confirmation, flow, and student engagement (Figure 1). In practice, mediators can causally influence one another and are interactable. To unravel how the three proposed mediation variables worked together to have a direct and indirect affect between the dependent and independent variables, additional supplemental analyses were performed. Hayes' (2013) serial multiple mediation model (6) was conducted to test the effects of a casual chain linking the three mediators from dependent and independent variables with hypothesised direction of flow (Figure 2).

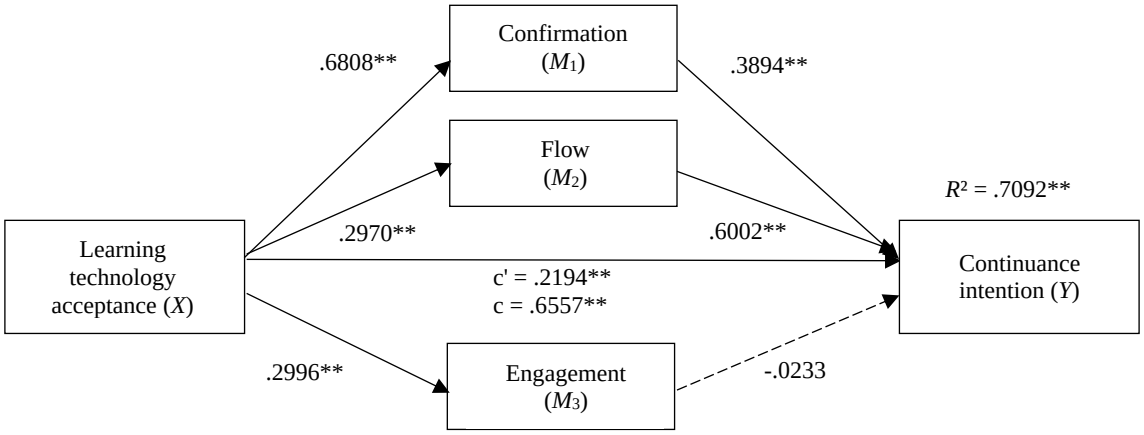

Figure 1. Parallel mediation model with path coefficients
Note. c' = direct effect of learning technology acceptance to continuance intention; c = total effect of learning technology acceptance to continuance intention. **$p < 0.01$.

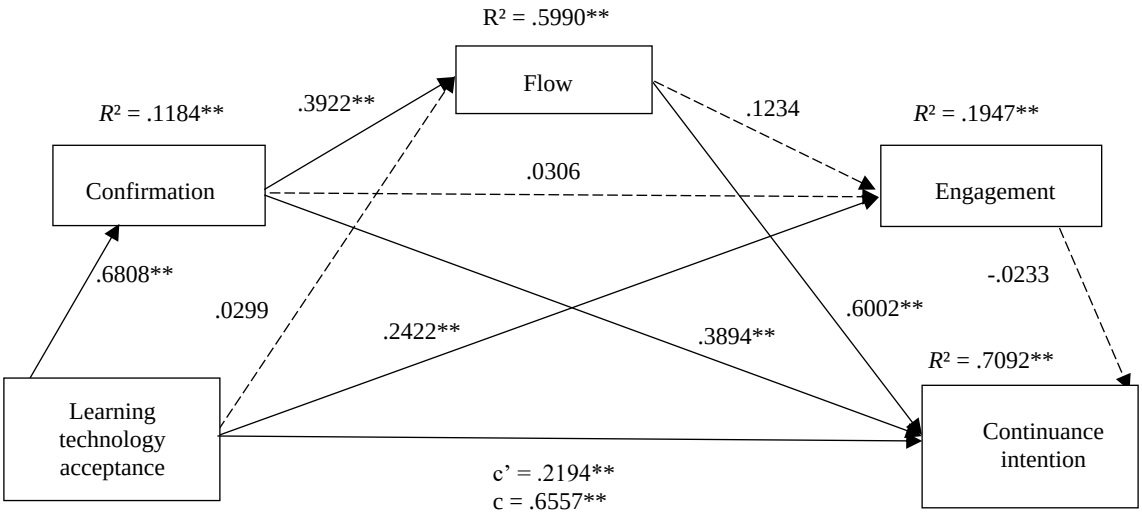

Figure 2. A statistical diagram of the serial mediation model with path coefficients
Note. c' = direct effect of learning technology acceptance to continuance intention; c = total effect of learning technology acceptance to continuance intention. **$p < 0.01$

Parallel mediation model

The results in Table 3 highlighted the mediation effects of three mediators (confirmation, flow, and student engagement) of students' learning technology acceptance and information systems continuance intention. As shown in Table 3, confirmation and flow mediated the effect the relationship between learning technology acceptance and continuance intention, therefore, H1 and H2 were supported. However, H3 was not supported.

Table 3
Mediation effects (bootstrapping 5000 samples)

Mediation path	Effect	BootLLCI	BootULCI	*p*-value	Mediation effect
H1: LTA→ CON→ CI	.2651	.1562	.3928	<.0001	Yes
H2: LTA→ FLOW→ CI	.1782	.0860	.2830	<.0001	Yes
H3: LTA→ SENG→ CI	-.0070	-.0585	.0517	.4380	No

Note. bootstrapping lower limit confidence interval (BootLLCI), bootstrapping upper limit confidence interval (BootULCI), learning technology acceptance (LTA); confirmation (CON); flow experience (FLOW); continuance intention (CI); student engagement (SENG)

In the parallel mediation model (Figure 1), the path coefficients based on 5000 bootstrapped samples (Figure 1 and Table 4) indicated that the direct effect (c') of learning technology acceptance on continuance intention was significant (B_{direct} = 0.2194, *SE* = 0.0691, $t(210) = 3.1751$, $p < .0001$), as was the total effect (c) of learning technology acceptance on continuance intention with three mediators (B_{total} = 0.6557, *SE* = 0.1040, $t(210) = 6.3027$, $p < .001$). The path coefficients in Table 4 show that the overall indirect effect (*B* = 0.4364, 95% CI = 0.2624 to 0.6102) was significant. Moreover, two out of three mediators in this parallel mediation model were found to significantly contribute to the overall indirect effect (LTA→ CONF→ CI; *B* = 0.2651, 95% CI = 0.1562 to 0.3928; LTA→ FLOW→ CI; *B* = 0.1782, 95% CI = 0.0860 to 0.2830). The direct effect from student engagement to continuance intention had a negative correlation and was not statistically significant (*B* = -0.0233, 95% CI = -0.1975 to 0.1509). In addition, the R^2 in the regression (R^2 = .7092, $F(4, 207) = 126.19$, $p < .0001$) indicated that the dependent variable and three mediators accounted for 70.92% of the variance in explaining continuance intention.

Table 4
Path coefficients, indirect effects, and 95% bias-corrected confidence interval predicting CI

Path	Effect	BootLLCI	BootULCI	*SE*	*t*	*p*-value
Direct effect (c'):	.2194	.0832	.3556	.0691	3.1751	.0017
LTA→ CONF	.6808	.4281	.9335	.1282	5.3115	<.0001
LTA→ FLOW	.2970	.1647	.4292	.0671	4.4263	<.0001
LTA→ SENG	.2996	.2021	.3972	.0495	6.0553	<.0001
CONF→ CI	.3894	.2905	.4883	.0502	7.7602	<.0001
FLOW→ CI	.6002	.4102	.7901	.0964	6.2284	<.0001
SENG → CI	-.0233	-.1975	.1509	.0884	-.2636	.7923
Indirect effect:	.4363	.2624	.6102	.0882		
LTA→ CONF→ CI	.2651	.1562	.3928	.0608		
LTA→ FLOW→ CI	.1782	.0860	.2830	.0500		
LTA→ SENG→ CI	-.0070	-.0585	.0517	.0281		
Total effect (c)	.6557	.4506	.8608	.1040	6.3027	<.0001

Note. bootstrapping lower limit confidence interval (BootLLCI), bootstrapping upper limit confidence interval (BootULCI), learning technology acceptance (LTA); confirmation (CON); flow experience (FLOW); continuance intention (CI); student engagement (SENG)

Serial mediation model

The next step is to test a serial mediation model (Figure 2). First, the model fit test was performed using AMOS and the results indicated good model fit according to the following indices: $\chi^2/df = 0.065$, TLI = 1.012, RMSEA = .000, SRMR = .011, GFI = .995, AGFI = .978 (Hu & Bentler, 1999). Figure 2 depicted the effects of a casual chain linking the three mediators from dependent and independent variables with a hypothesised direction of flow (LTA→ CONF→ FLOW→ SENG→ CI). The results from the serial mediation model indicated that the three mediators mediated the relationships between learning technology acceptance and continuance intention with a high ratio (0.6655, 95% CI = 0.2635 to 0.6085) of the overall indirect effect to the total effect. Considering the direct effects, learning technology acceptance had a positive and significant relationships with confirmation (B = 0.6808, SE = 0.1282, p <.001) and student engagement (B = 0.2422, SE = 0.0516, p <.001), but not with flow (B = 0.0299, SE = 0.0474, p = .529). Moreover, student engagement did not have strong relationships to other variables. Only the path between learning technology acceptance and student engagement was significant. Surprisingly, student engagement was negatively related to continuance intention (B = -0.0233, SE = 0.0884, p = .7923), suggesting that students with higher engagement in academic life showed lower intention to continue using the Top Hat mobile app in their future learning.

Confirmation as a mediating variable was shown to be the most important link between the independent variable (LTA→ CONF, B = 0.6808, SE = 0.1282, p <.001), dependent variable (CONF→ CI; B = 0.3894, SE = 0.0502, p <.001), and one other mediator (CONF→ FLOW; B = 0.3922, SE = 0.0240, p <.001). In addition, Table 5 shows that this serial mediation model yielded two significant indirect paths (LTA→ CONF→ CI; LTA→ CONF→ FLOW→ CI) among seven possible paths linking from learning technology acceptance to continuance intention. First, it is worthy to note that the indirect effect of learning technology acceptance on continuance intention via mediation by confirmation (LTA→ CONF→ CI; B = 0.2651, 95% CI = 0.0593 to 0.1559) was stronger than the direct effect of learning technology acceptance on continuance intention (B_{direct} = 0.2194; 95% CI = 0.0832 to 0.3556), suggesting that confirmation did strongly mediate the relationship between learning technology acceptance and continuance intention. Next, this serial mediation model also yielded the other significant indirect path (LTA→ CONF→ FLOW→ CI; B = 0.1603, 95% CI = 0.0384 to 0.0907). This finding revealed that learning technology acceptance could increase confirmation, which in turn increases flow experience and thus increases continuance intention.

Table 5
Path coefficients of indirect effects on the serial mediation model

Path	Effect	BootLLCI	BootULCI	*SE*
Total indirect effect:	.4364	.2635	.6085	.0874
LTA → CONF → CI	.2651	.1559	.3891	.0593
LTA → FLOW → CI	.0180	-.0382	.0773	.0293
LTA → SENG → CI	-.0056	-.0468	.0440	.0226
LTA → CONF → FLOW → CI	.1603	.0907	.2414	.0384
LTA → CONF → SENG → CI	-.0005	-.0092	.0057	.0033
LTA → FLOW → SENG → CI	-.0001	-.0020	.0015	.0008
LTA → CONF → FLOW → SENG → CI	-.0008	-.0086	.0062	.0035

Note. bootstrapping lower limit confidence interval (BootLLCI), bootstrapping upper limit confidence interval (BootULCI), learning technology acceptance (LTA); confirmation (CON); flow experience (FLOW); continuance intention (CI); student engagement (SENG)

Discussion

The aim of this study was to examine the mediation effects of three mediators (confirmation, flow, and student engagement) of students' learning technology acceptance and information systems continuance intention while exploring the functions of these variables in the mediating process between learning technology acceptance and continuance intention. First, utilising the bootstrapping procedure suggested by Hayes (2013), the results from our data supported two of the three proposed hypotheses. Our findings revealed that business students' confirmation and flow experience elicited by the m-learning app, are two important mediating factors connected to their decisions on continue usage of the technology.

Based on results from the parallel and serial mediation model using bootstrapping methods, several key findings emerged. First, two mediators were found to mediate the relationships between learning technology acceptance and continuance intention with a combined high ratio (0.6655) of the overall indirect effect to the total effect. In consonance with Lin et al.'s (2020) and Cheng's (2020) research findings, confirmation and flow in this study were indicated as statistically significant mediators can influence users' intention to continue using the system. Furthermore, our results not only revealed confirmation in this serial mediation model as a first step toward promoting students' flow experience, but also highlighted its vital role in increasing students' information systems continuance intention. In supporting conclusions in Cheng's (2020) research, findings in this study also suggested business students who indicated confirmation of expectations toward the m-learning system were more likely to experience flow state by attracting to and showing intrinsic interests in the learning process, and subsequently led to their continuance intention of future system usages. In summary, experiencing flow encourages a person to be continual and persistent at focusing on an activity (Nakamura & Csikszentmihalyi, 2002), which literature reveals as an important attribute for students' learning process and information systems continuance intention (Cheng, 2020; Liu et al., 2018; Yang & Lee, 2018).

Interestingly, although insignificant, our results showed the level of student engagement was associated with a slight negative effect on the level of system continuance intention. Moreover, all indirect paths from learning technology acceptance to continuance intention linked through student engagement had slight negative coefficients, revealing the reduction in continuance intention through the increase in the levels of various combinations of confirmation, student engagement, and flow. One possible explanation would be that the single dimensional construct we adopted in measuring student engagement cannot precisely capture and explain its complexities in the m-learning context. Researchers argue that engagement is highly dynamic, fluctuating, interactive, and context-dependent (Goldin et al., 2011). Thus, it is a multi-faceted concept emphasising different components of student involvement in the learning process. Therefore, the effect of student engagement needs more research attention in the future.

Implications for practice and research

This study brings several practical values and implications to the m-learning context. First, the statistical findings in this study imply that business students' confirmation and flow experience elicited by the m-learning app aids in understanding of their intention to continue using the system providing empirical

evidence to encourage university administrators, instructors, and instructional designer to implement such initiatives. Specifically, the Covid-19 outbreak poses a significant challenge to educational administrators, educators, and instructional designers to make emergency transitions to support student learning (Essa et al., 2020; Henriksen et al., 2020; Secundo et al., 2021) regardless of course delivery modalities. With the Covid-19 pandemic, there is more reliance on ICTs which can deliver high-quality and accessible content, such as m-learning technologies that can provide clear and accurate communication and can work as a cognitive tool to catalyse enjoyments in active learning environments (Al-Emran, 2020; Dwikoranto et al., 2020).

Second, another prominent finding of this study is that confirmation as the first mediating variable in this serial mediation model plays a vital role in the chains of causality. Therefore, it is imperative for instructors and educational technology designers to make sure that students have positive confirmation and an enjoyable experience with m-learning. To achieve this goal, we recommend that instructors develop partnerships with instructional designers in multiple areas, such as selecting high quality m-learning applications and developing effective learning interventions through the following strategies.

Adoption of a comprehensive rubric can support educators as a valid and learning theory-based tool to make it efficient, objective, and consistent to analyse quality of m-learning apps. According to Lee and Cherner (2015), a variety of instructional apps are being developed every day and each serves a specific purpose in student learning and engagement. Thus, without an evaluative instrument to identify quality apps utilised in the classroom, it can quickly become a guessing game for instructors, and they can risk wasting students' time with inferior apps. Assisting instructors to develop mobile-friendly and accessible contents can ensure students' positive confirmation toward the system. While innovative ICTs can effectively engage and motivate students in learning, use of technology without effective and appropriate pedagogies may distract students learning and cause a shortage of time for learning tasks (Bragdon & Dowler, 2016; Rashid & Asghar, 2016). Thus, instructors must collaborate with instructional designers in the orchestrating of mobile technologies and learning content to increase students' willingness in accepting m-learning technology and to leverage students' flow experience while using the system. The use of authentic content and activities scaffolded to adequately create a zone of proximal development (Parsons & MacCallum, 2017) and to support active learning which will spark students' interests in consistent learning (Shih & Tsai, 2017).

Third, in terms of the implications for research, this study contributes to the literature on IS continuance intention of using m-learning apps by examining the magnitude and significance of hypothesised causal connections between learning technology acceptance and continuance intention, the three mediators of confirmation, flow, and student engagement. This is the first study in the m-learning context using a serial multiple mediation model to elucidate the chains of causality and the underlying mechanisms of these three mediated cognitive learning factors.

Conclusion

This study aimed to contribute to the existing literature on IS continuance intention. The research responded to calls to study the users' IS continuance intention (Nabavi et al., 2016) focusing on mobile applications (apps) in learning. This study recognised that the continuous use of the m-learning app is driven not only by students' flexible thinking skills in accepting new learning technology, but also by a set of cognitive attributes reflecting users' positive experiences with the system. The findings indicated that learning technology acceptance plays a key role in the digital natives' learning. Learning technology acceptance along with confirmation, were shown to be two antecedents in influencing students' concentration and enjoyment in the learning process, as well as impacting student decision-making regarding the continuance decision in accepting new m-learning system. In other words, students who have positive mindsets in accepting new technology will try their best to overcome challenges from learning unfamiliar technology, which in turn, leads them to making a continuance decision in m-learning usage.

Limitations and future research directions

The primary limitation of this study is that the data were collected from graduate and undergraduate students in the business program at a single university. Caution should be taken in generalising from this study to students who studied in different programs or at different institutions. Therefore, it is suggested that future

studies should try to collect data across disciplines or institutions. Moreover, students' flow experience in the m-learning environment can also be influenced by the teaching strategies and pedagogical interventions that the instructors were implementing in their course design. Hence, it is important to consider and control the design of courses and how courses are taught as data is collected in future studies. Another limitation is that all variables in this study were measured utilising survey instruments which may cause common method bias. Thus, Harman's (1976) single factor test was conducted and further assured that common method bias does not affect our results. Moreover, our measures of learning technology acceptance, confirmation, flow, student engagement, and continuance intention were based on retrospective self-reports. Thus, response bias itself can arise from student's perspectives in cognitive learning experiences and their feelings regarding innovative learning technologies at the time the survey was completed. It is suggested that future studies should adopt various sources to measures students' human-computer interactions and use observation techniques in determining students' actual learning engagement. In addition, with the unique features of usage logs provided through m-learning system, researchers may consider using learning analytics techniques to collect rich, multifaceted, and process-oriented learner data (Viberg et al., 2020) to examine and visualise learners' cognitive learning behaviours.

References

Al-Emran, M. (2020). Editorial. Mobile learning during the era of COVID-19. *Revista Virtual Universidad Católica del Norte*, *61*, 1-2. https://www.doi.org/10.35575/rvucn.n61a1

Al-Emran, M., Arpaci, I., & Salloum, S. A. (2020). An empirical examination of continuous intention to use m-learning: An integrated model. *Education and Information Technologies*, *25*, 2899–2918. https://doi.org/10.1007/s10639-019-10094-2

Alexopoulou, A., Batsou, A., & Drigas, A. (2020). Mobiles and cognition: The associations between mobile technology and cognitive flexibility. *International Journal of Interactive Mobile Technologies*, *14*(3), 146-156. https://doi.org/10.3991/ijim.v14i03.11233

Alioon, Y., & Delialioğlu, Ö. (2019). The effect of authentic m-learning activities on student engagement and motivation. *British Journal of Educational Technology*, *50*(2), 655-668. https://doi.org/10.1111/bjet.12559

Almaiah, M. A., & Al Mulhem, A. (2019). Analysis of the essential factors affecting of intention to use of mobile learning applications: A comparison between universities adopters and non-adopters. *Education and Information Technologies*, *24*(2), 1433-1468. https://doi.org/10.1007/s10639-018-9840-1

Al-Maroof, R. S., & Salloum, S. A. (2021). An integrated model of continuous intention to use of Google Classroom. In M. Al-Emran, K. Shaalan, & A. Hassanien (Eds.) *Recent advances in intelligent systems and smart applications*. *Studies in systems, decision and control* (Vol. 295, pp. 311-335). Springer. https://doi.org/10.1007/978-3-030-47411-9_18

Anohah, E., Oyelere, S. S., & Suhonen, J. (2017). Trends of mobile learning in computing education from 2006 to 2014: A systematic review of research publications. *International Journal of Mobile and Blended Learning*, *9*(1), 16-33. https://doi.org/10.4018/IJMBL.2017010102

Baker-Eveleth, L., & Stone, R. W. (2015). Usability, expectation, confirmation, and continuance intentions to use electronic textbooks. *Behaviour & Information Technology*, *34*(10), 992-1004. https://doi.org/10.1080/0144929X.2015.1039061

Barak, M. (2018). Are digital natives open to change? Examining flexible thinking and resistance to change. *Computers & Education*, *121*, 115–123. https://doi.org/10.1016/j.compedu.2018.01.016

Barak, M., & Levenberg, A. (2016a). A model of flexible thinking in contemporary education. *Thinking Skills and Creativity*, *22*, 74-85. https://doi.org/10.1016/j.tsc.2016.09.003

Barak, M., & Levenberg, A. (2016b). Flexible thinking in learning: An individual differences measure for learning in technology-enhanced environments. *Computers & Education*, *99*, 39-52. https://doi.org/10.1016/j.compedu.2016.04.003

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, *25*(3), 351-370. https://doi.org/10.2307/3250921

Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quarterly*, *28*(2), 229–254. https://doi.org/10.2307/25148634

Bragdon, R. A., & Dowler, K. (2016). College student technology use and academic performance. *International Journal of Humanities and Social Science*, *6*(1), 12-22.

Cañas, J., Quesada, J., Antoli, A., & Fajardo, I. (2003). Cognitive flexibility and adaptability to environmental changes in dynamic complex problem-solving tasks. *Ergonomics*, *46*(5), 482-501. https://doi.org/10.1080/0014013031000061640

Chang, C.-C. (2013). Exploring the determinants of e-learning systems continuance intention in academic libraries. *Library Management*, *34*(1/2), 40–55. https://doi.org/10.1108/01435121311298261

Chang, C.-C., Liang, C., Chou, P.-N., & Lin, G.-Y. (2016). Is game-based learning better in flow experience and various types of cognitive load than non-game-based learning? Perspective from multimedia and media richness. *Computers in Human Behavior, 71*, 218-227. https://doi.org/10.1016/j.chb.2017.01.031

Chen, C. C., & Huang, T. C. (2012). Learning in a u-museum: Developing a context-aware ubiquitous learning environment. *Computers & Education*, *59*(3), 873-883. https://doi.org/10.1016/j.compedu.2012.04.003

Chen, L., Meservy, T. O., & Gillenson, M. (2012). Understanding information systems continuance for information-oriented mobile applications. *Communications of the Association for Information Systems*, *30*(1), Article 9. https://doi.org/*10.17705/1CAIS.03009*

Cheng, Y. M. (2020). Investigating medical professionals' continuance intention of the cloud-based e-learning system: an extension of expectation–confirmation model with flow theory. *Journal of Enterprise Information Management*, *34*(4), 1169-1202. https://doi.org/10.1108/JEIM-12-2019-0401

Cohen, J. D., McClure, S. M., & Yu, A. J. (2007). Should I stay or should I go? How the human brain manages the trade-off between exploitation and exploration. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *362*(1481), 933-942. https://doi.org/10.1098/rstb.2007.2098

Crompton, H. (2013). A historical overview of mobile learning: Toward learner-centered education. In Z. L. Berge, & L. Y. Muilenburg (Eds.). *Handbook of Mobile Learning* (pp. 3–14). Routledge.

Csikszentmihalyi, M. (1975). *Beyond boredom and anxiety*. Jossey-Bass.

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. HarperCollins.

Csikszentmihalyi, M., & Csikszentmihalyi, I. (Eds.). (1988). *Optimal experience: Psychological studies of flow in consciousness*. Cambridge University Press.

Dai, H. M., Teo, T., Rappa, N. A., & Huang, F. (2020). Explaining Chinese university students' continuance learning intention in the MOOC setting: A modified expectation confirmation model perspective. *Computers & Education*, *150*, 103850. https://doi.org/10.1016/j.compedu.2020.103850

Dalvi-Esfahani, M., Wai Leong, L., Ibrahim, O., & Nilashi, M. (2020). Explaining students' continuance intention to use mobile Web 2.0 learning and their perceived learning: An integrated approach. *Journal of Educational Computing Research*, *57*(8), 1956–2005. https://doi.org/10.1177/0735633118805211

Dawoud, H. M., Al-Samarraie, H., & Zaqout, F. (2015). The role of flow experience and CAD tools in facilitating creative behaviours for architecture design students. *International Journal of Technology and Design Education*, *25*, 541–561. https://doi.org/10.1007/s10798-014-9294-8

Dwikoranto, D., Setiani, R., Prahani, B. K., & Mubarok, H. (2020). Mobile learning to improve student collaborative skills: An alternative to online learning in the era of Covid-19 pandemic. *Jurnal Penelitian dan Pengkajian Ilmu Pendidikan: e-Saintika*, *4*(3), 259-271. https://doi.org/10.36312/e-saintika.v4i3.314

Essa, M. M., Subramanian, K. P., & Jayasuriya, H. P. (2020). COVID-19 impact on undergraduate education: Academicians' perspective. *Journal of Health and Allied Sciences*, *10*(3), 138-140. https://doi.org/10.1055/s-0040-1718609

Goldin, G. A., Epstein, Y. E., Schorr, R. Y., & Warner, L. B. (2011). Beliefs and engagement structures: Behind the affective dimension of mathematical learning. *ZDM Mathematics Education*, *43*(4), 547-560. http://dx.doi.org/10.1007/s11858-011-0348-z

Guo, Z., Xiao, L., Van Toorn, C., Lai, Y., & Seo, C. (2016). Promoting online learners' continuance intention: An integrated flow framework. *Information & Management*, *53*(2), 279–295. https://doi-org.lib-proxy.jsu.edu/10.1016/j.im.2015.10.010

Hamari, J., Shernoff, D. J., Rowe, E., Coller, B., Asbell-Clarke, J., & Edwards, T. (2016). Challenging games help students learn: An empirical study on engagement, flow and immersion in game-based learning. *Computers in Human Behavior*, *54*, 170-179. https://doi.org/10.1016/j.chb.2015.07.045

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

Harman, H. H. (1976). *Modern factor analysis*. University of Chicago Press.
Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis*. *A regression-based approach*. The Guilford Press.
Henriksen, D., Creely, E., & Henderson, M. (2020). Folk pedagogies for teacher transitions: Approaches to synchronous online learning in the wake of COVID-19. *Journal of Technology and Teacher Education*, *28*(2), 201-209. https://www.learntechlib.org/primary/p/216179/
Hossain, M. N., Talukder, M. S., Khayer, A., & Bao, Y. (2020). Investigating the factors driving adult learners' continuous intention to use m-learning application: A fuzzy-set analysis. *Journal of Research in Innovative Teaching & Learning*, *14*(2), 125-270. https://doi.org/10.1108/JRIT-09-2019-0071
Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1-55. https://doi.org/10.1080/10705519909540118
Huang, C.-K., Chen, C.-D., & Liu, Y.-T. (2019). To stay or not to stay? Discontinuance intention of gamification apps. *Information Technology & People*, *32*(6), 1423-1445. https://doi.org/10.1108/ITP-08-2017-0271
Huang, C.-Y., Sun, J. C.-Y., & Yu, P.-T. (2015). The benefit of a challenge: Student motivation and flow experience in tablet-PC-game-based learning. *Interactive Learning Environment*, *23*(2), 172-190. https://doi.org/10.1080/10494820.2014.997248
Hwang, G. J., Lai, C. L., Liang, J. C., Chu, H. C., & Tsai, C. C. (2018). A long-term experiment to investigate the relationships between high school students' perceptions of mobile learning and peer interaction and higher-order thinking tendencies. *Educational Technology Research and Development*, *66*(1), 75-93. https://doi.org/10.1007/s11423-017-9540-3
Ifinedo, P. (2017). Students' perceived impact of learning and satisfaction with blogs. *International Journal of Information and Learning Technology*, *34*(4), 322-337. https://doi.org/10.1108/IJILT-12-2016-0059
Joo, Y. J., So, H. J., & Kim, N. H. (2018). Examination of relationships among students' self-determination, technology acceptance, satisfaction, and continuance intention to use K-MOOCs. *Computers & Education*, *122*, 260-272. https://doi.org/10.1016/j.compedu.2018.01.003
Kang, K.-S., & Kim, H.-C. (2018). Testing the mediating effects of flow in the structural relationship among contents quality, telepresence, and continuous intention to use e-learning services. *E-Trade Review*, *16*(1), 19–40. https://doi.org/10.17255/etr.16.1.201802.19
Kaur, P., Dhir, A., Chen, S., & Rajala, R. (2016). Flow in context: Development and validation of the flow experience instrument for social networking. *Computers in Human Behavior*, *59*, 358-367. https://doi.org/10.1016/j.chb.2016.02.039
Khan, I. U., Hameed, Z., Yu, Y., & Khan, S. U. (2017). Assessing the determinants of flow experience in the adoption of learning management systems: the moderating role of perceived institutional support. *Behaviour & Information Technology*, *36*(11), 1162-1176. https://doi.org/10.1080/0144929X.2017.1362475
Kim, H. J., Yi, P., & Hong, J. I. (2020). Students' academic use of mobile technology and higher-order thinking skills: The role of active engagement. *Education Sciences*, *10*(3), 47-62. https://doi.org/10.3390/educsci10030047
Lam, S. F., & Jimerson, S. R. (2008). *Exploring student engagement in schools internationally: Consultation paper*. International School Psychologist Association.
Lee, C-Y., & Cherner, T. S. (2015). A comprehensive evaluation rubric for assessing instructional apps. *Journal of Information Technology Education: Research, 14*, 21-53. http://www.jite.org/documents/Vol14/JITEV14ResearchP021-053Yuan0700.pdf
Lee, M. C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model. *Computers & Education*, *54*(2), 506-516. https://doi.org/10.1016/j.compedu.2009.09.002
Li, J., Liu, X., Ma, L., & Zhang, W. (2019). Users' intention to continue using social fitness-tracking apps: expectation confirmation theory and social comparison theory perspective. *Informatics for Health and Social Care*, *44*(3), 298-312. https://doi.org/10.1080/17538157.2018.1434179
Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information system continuance. *MIS Quarterly*, *31*(4), 705-737. https://doi.org/10.2307/25148817
Lin, J., Lin, S., Turel, O., & Xu, F. (2020). The buffering effect of flow experience on the relationship between overload and social media users' discontinuance intentions. *Telematics and Informatics*, *49*, 1-18. https://doi.org/10.1016/j.tele.2020.101374

Lin, T. C., Huang, S. L., & Hsu, C. J. (2015). A dual-factor model of loyalty to IT product – The case of smartphones. *International Journal of Information Management*, *35*(2), 215-228. https://doi.org/10.1016/j.ijinfomgt.2015.01.001

Lin, W.-S. (2012). Perceived fit and satisfaction on web learning performance: IS continuance intention and task-technology fit perspectives. *International Journal of Human-Computer Studies*, *70*(7), 498-507. https://doi.org/10.1016/j.ijhcs.2012.01.006

Liu, Y., Liu, D., Yuan, Y., & Archer, N. (2018). Examining situational continuous mobile game play behavior from the perspectives of diversion and flow experience. *Information Technology & People*, *31*(4), 948-965. https://doi.org/10.1108/ITP-02-2016-0042

Lu, Y., Wang, B., & Lu, Y. (2019). Understanding key drives of MOOC satisfaction and continuance intention to use. *Journal of Electronic Commerce Research*, *20*(2), 105-117. http://www.jecr.org/sites/default/files/2019vol20no2_Paper3.pdf

Nabavi, A., Taghavi-Fard, M. T., Hanafizadeh, P., & Taghva, M. R. (2016). Information technology continuance intention: A systematic literature review. *International Journal of E-Business Research*, *12*(1), 58-95. https://doi.org/10.4018/IJEBR.2016010104

Nakamura, J., & Csikszentmihalyi, M. (2002). The concept of flow. In C. Snyder, & S. Lopez (Eds.), *Handbook of positive psychology* (pp. 89-105). University Press.

Notari, M. P., Hielscher, M., & King, M. (2016). Educational apps ontology. In D. Churchill, J. Lu, T. Chiu, & B. Fox (Eds.), *Mobile learning design* (pp. 83-96). Springer. https://doi.org/10.1007/978-981-10-0027-0_5

Park, J., Parsons, D., & Ryu, H. (2010). To flow and not to freeze: Applying flow experience to mobile learning. *IEEE transactions on Learning Technologies*, *3*(1), 56-67. https://doi.org/10.1109/TLT.2010.1

Parsons, D., & MacCallum, K. (2017). A learning theory rubric for evaluating mobile learning activities. *International Journal of Online Pedagogy and Course Design*, *7*(4), 24-38.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(1), 879–891. https://doi.org/10.3758/BRM.40.3.879

Rashid, T., & Asghar, H. M. (2016). Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. *Computers in Human Behavior*, *63*, 604–612. https://doi.org/10.1016/j.chb.2016.05.084

Ruiz-Mafe, C., Martí-Parreño, J., & Sanz-Blas, S. (2014). Key drivers of consumer loyalty to Facebook fan pages. *Online Information Review*, *38*(3), 362-380. https://doi.org/10.1108/OIR-05-2013-0101

Ryu, H., & Parsons, D. (2012). Risky business or sharing the load? Social flow in collaborative mobile learning. *Computers & Education*, *58*(2), 707-720. https://doi.org/10.1016/j.compedu.2011.09.019

Saedi, N., Taghizade, A., & Hatami, J. (2018). The effect of mobile learning applications on students' high-level cognitive skills. *Interdisciplinary Journal of Virtual Learning in Medical Sciences*, *9*(4). https://doi.org/10.5812/ijvlms.69203

Secundo, G., Mele, G., Vecchio, P. D., Elia, G., Margherita, A., & Ndou, V. (2021). Threat or opportunity? A case study of digital-enabled redesign of entrepreneurship education in the COVID-19 emergency. *Technological Forecasting and Social Change*, *166*, 120565. https://doi.org/10.1016/j.techfore.2020.120565

Shih, W. L, & Tsai, C. Y. (2017). Students' perception of a flipped classroom approach to facilitating online project-based learning in marketing research courses. *Australasian Journal of Educational Technology*, *33*(5), 32-49. https://doi.org/10.14742/ajet.2884

Spiro, R. J., & Jehng, J. C. (1990). Cognitive flexibility and hypertext: Theory and technology for the nonlinear and multidimensional traversal of complex subject matter. In D. Nix & R. Spiro (Eds.), *Cognition, education, and multimedia: Exploring ideas in high technology* (pp. 163-204). Lawrence Erlbaum Associates.

Thong, J. Y. L., Hong, S.-J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human-Computer Studies*, *64*(9), 799–810. https://doi.org/10.1016/j.ijhcs.2006.05.001

Tsai, Y. H., Lin, C. H., Hong, J. C., & Tai, K. H. (2018). The effects of metacognition on online learning interest and continuance to learn with MOOCs. *Computers & Education*, *121*, 18-29. https://doi.org/10.1016/j.compedu.2018.02.011

Tseng, H., & Hill, L. (2020). The impact of high-fidelity simulation on nursing students' flexible and reflective thinking in higher education. *Higher Learning Research Communications*, *10*(2), 52–65. https://doi.org/10.18870/hlrc.v10i2.1196

Tseng, H., Kuo, Y. C. & Walsh, E. J. (2020). Exploring first-time online undergraduate and graduate students' growth mindsets and flexible thinking and their relations to online learning engagement. *Education Technology Research and Development, 68*, 2285-2303. https://doi.org/10.1007/s11423-020-09774-5

Viberg, O., Wasson, B., & Kukulska-Hulme, A. (2020). Mobile-assisted language learning through learning analytics for self-regulated learning (MALLAS): A conceptual framework. *Australasian Journal of Educational Technology*, *36*(6), 34-52. https://doi.org/10.14742/ajet.6494

Webster, J., Trevino, L. K., & Ryan, L. (1993). The dimensionality and correlates of flow in human-computer interactions. *Computers in Human Behavior*, *9*(4), 411-426. https://doi.org/10.1016/0747-5632(93)90032-N

Witmer, B. G., & Singer, M. J. (1998). Measuring presence in virtual environments: A presence questionnaire. *Presence: Teleoperators and Virtual Environments*, *7*(3), 225–240. https://doi.org/10.1162/105474698565686

Yang, H., & Lee, H. (2018). Exploring user acceptance of streaming media devices: An extended perspective of flow theory. *Information Systems and E-Business Management*, *16*, 1–27. https://doi.org/10.1007/s10257-017-0339-x

Ye, Q., Luo, Y., Chen, G., Guo, X., Wei, Q., & Tan, S. (2019). Users intention for continuous usage of mobile news apps: The roles of quality, switching costs, and personalization. *Journal of Systems Science and Systems Engineering*, *28*(1), 91-109. https://doi.org/10.1007/s11518-019-5405-0

Zhou, T. (2012). Understanding the effect of flow on user adoption of mobile games. *Personal and Ubiquitous Computing*, *17*(4), 741-748. https://doi.org/10.1007/s00779-012-0613-3

Zhou, T., & Liu, Y. (2014). Examining continuance usage of mobile banking from the perspectives of ECT and flow. *International Journal of Services Technology and Management*, *20*(4-6), 199-214. https://doi.org/10.1504/IJSTM.2014.068844

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Appendix A
Survey instrument

Scales	Item text
Learning technology acceptance	1. I adjust quickly to new learning technology. 2. I adjust easily to technological changes as software updates. 3. I am open to update in new technological tools that can help me learn. 4. I use various technological tools for learning and frequently change between them. 5. I like to experience new learning technologies.
Confirmation	1. Overall, the benefits received from the Top Hat app were… (1 = much less than expected; 7 = much greater than expected). 2. My overall experience with the Top Hat app was… (1 = much worse than expected; 7 = much better than expected). 3. The problems encountered with the Top Hat app were… (1 = much more serious than expected; 7 = much less serious than expected).
Flow experience	1. When using the Top Hat app, I felt in control over everything. 2. I felt that I had no control over my learning process with the Top Hat app. 3. The Top Hat app allowed me to control the whole learning process. 4. When using the Top Hat app, I thought about other things. 5. When using the Top Hat app, I was aware of distractions. 6. When using the Top Hat app, I was totally absorbed in what I was doing. 7. Using the Top Hat app excited my curiosity. 8. Interacting with the Top Hat app made me curious. 9. Using the Top Hat app aroused my imagination. 10. Using the Top Hat app bored me. 11. Using the Top Hat app was intrinsically interesting. 12. The Top Hat app was fun for me to use.
Student Engagement in Schools Questionnaire	1. When I study, I try to understand the material better by relating it to things I already know. 2. When I study, I figure out how the information might be useful in the real world. 3. When learning new information, I try to put the ideas in my own words. 4. When I study, I try to connect what I am learning with my own experiences. 5. I make up my own examples to help me understand the important concepts I learn from school. 6. When learning things for school, I try to see how they fit together with other things I already know. 7. When learning things for school, I often try to associate them with what I learnt in other classes about the same or similar things. 8. I try to see the similarities and differences between things I am learning for school and things I know already. 9. I try to understand how the things I learn in school fit together with each other. 10. I try to match what I already know with things I am trying to learn for school. 12. I try to think through topics and decide what I'm supposed to learn from them, rather than studying topics by just reading them over. 13. When studying, I try to combine different pieces of information from course material in new ways.