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Modelling the effects of self-regulation, perceived usefulness, confirmation and satisfaction on the continuous intention to utilise mobile learning applications

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Although m-learning applications have been widely used in universities, the factors that might affect the continuous intention to utilise them have not been fully addressed. Therefore, this study aimed to understand this by extending the expectation confirmation model (ECM) and incorporating self-regulated learning (SRL). A quantitative research design was adopted, and data were gathered using a structured questionnaire distributed to 227 undergraduate university students through simple random sampling. The data were analysed using structural equation modelling (SEM) in AMOS. The findings revealed that the proposed model has high explanatory power (79%), which explains the phenomena of influential factors. Additionally, students' perceived usefulness (PU) and satisfaction had a positive direct significant effect on students' continuous intention to use m-learning applications. However, perceived usefulness did not affect satisfaction but confirmation did. Furthermore, SRL had an indirect positive effect on continuous intention, while it had a direct significant effect on both perceived usefulness and confirmation. The practical and theoretical implications of this study are further discussed in detail.

KEYWORDS

m-learning applications, continuance intention, ECM, self-regulated learning, satisfaction, perceived usefulness

Introduction

The establishment of mobile devices has resulted in the quick advancement of mobile learning applications. Advances in mobile tihnologies and networking communications have changed people's learning methods and lives (Chao, 2019; Liu et al., 2021a). Several researchers have stated that the integration of learning online and mobile learning applications is an essential aspect for both students and instructors (Hoi, 2020; Alshurideh et al., 2023). Due to the increased utilisation of mobile devices, their utilisation for learning has increased widely, and many mobile learning applications have been developed (Alshurideh et al., 2023). Learning via m-learning applications enables people to learn without limitations in space or time, which boosts their learning effectiveness and intentions (Liu et al., 2021b).

M-learning applications have been developed for the purpose of teaching specific knowledge and have become popular among university students (Hoi, 2020). There are several advantages to utilising m-learning applications, such as their flexibility, portability, accessibility and dealing with learners individually (Sung et al., 2015; Chen, 2018). For promoting learning and achieving educational objectives, some of these m-learning applications are designed specifically, such as situational mode, embedding engagement mode, providing recommendation services and including gamification (Chen, 2018; Reinders and Pegrum, 2017). These m-learning applications offer learners a convenient service, such as learning different tasks, examinations, preparing to work, etc. Some studies have assessed the effectiveness of m-learning platforms (Papadima-Sophocleous et al., 2012; Lee and Sylvén, 2021). For instance, in m-learning applications utilised for English learning, scholars have stated that m-learning assisted learners with reading and pronunciation (Cao and Deng, 2019), writing (Li and Hegelheimer, 2013), learning vocabulary (Klimova, 2021) and communication skills (Lee and Sylvén, 2021).

Based on the above-mentioned findings, it is confirmed that m-learning applications could offer huge benefits for learners, which can cultivate a positive attitude among learners towards using them (Yang and Wang, 2019). However, some learners still prefer learning through non-tech applications, such as physical books (Nie et al., 2020), which leads to the question that offering m-learning applications for learners might not necessarily lead to a continued intention to use them.

Furthermore, offering m-learning applications has some complexities that require careful consideration to maintain their effectiveness and lead to a continued desire to be used by learners (Obeid et al., 2024). One of these obstacles is ensuring that learners remain motivated to utilise m-learning applications. Thus, further studies are essential to assess the variables that may affect learners' continued intention to utilise these m-learning applications (Foo et al., 2021; Obeid et al., 2024). Many scholars have stated that further understanding is needed regarding the influential factors that might affect or hinder students' continuous intention to utilise m-learning (Goh and Yang, 2021; Obeid et al., 2024).

Additionally, to maintain the progress of m-learning applications and achieve their desired objectives, academics and decision-makers should investigate the variables that may affect students' continued intention to utilise these m-learning applications. Furthermore, assessing and identifying the variables that may affect students' continued intention to utilise m-learning applications would help decision-makers comprehend these influential factors and encourage them to develop solutions for addressing the obstacles. Thus, this study proposes a model for assessing the variables that might affect students' continuous intention to utilise m-learning applications. The ECM is one of the most popular models utilised to examine users' continuous intentions to use a specific technology (Mouakket, 2018).

Based on ECM, confirmation, PU and satisfaction are the main variables that are associated with users' continuous intention to utilise information systems. In learning through technologies context, many researchers have confirmed that PU and confirmation predict users' satisfaction, which leads to a higher continuous intention to utilise technologies (Joo et al., 2011; Alshammari and Alshammari, 2024). However, many other factors could play a role and affect students' intentions. Students' self-regulation focuses on their behaviour to monitor and control the learning process, which enables them to reach their educational goals.

To our knowledge, no study has combined ECM with self-regulation to assess its effects on students' continuous intention to utilise m-learning applications. Thus, this study proposes a theoretical model relying on ECM and combines additional variables, namely self-regulation, to assess their effects on students' continued intention to utilise m-learning applications.

This study makes two contributions. It theoretically advances the ECM framework by adding a learner centered variable, broadening and expanding its intended use in educational research field. This innovation bridges the gap between theories of user satisfaction and self-directed learning paradigms. The findings of this research also have practical implications for educators, instructional designers, and developers of m-learning applications. With a deeper understanding about how self-regulation influences prolonged engagement, stakeholders could build more adaptive, more effective learning systems to aid students in intervening on their way toward their educational goals. Therefore, this study provides the foundation for developing user friendly but pedagogically robust m-learning environments, which, in turn, will promote the long term adoption and enhanced learning outcomes.

Literature review and research model

Mobile learning applications aim at providing convenience to gain knowledge for learners (Hoi, 2020). The huge demands of these mobile applications have resulted in a rapid expansion to contain other apps such as e-books, games, entertainment, social media platforms and finance (Hsu and Lin, 2015). Recently, the number of learners using mobile learning applications for several learning objectives has increased rapidly (Chen, 2018; Nie et al., 2020). Students at universities are considered the largest users of these mobile learning applications (Liu et al., 2021a). Although the utilisation of mobile learning apps among students is widely increased (Bian and Liu, 2017), they could provide huge benefits in terms of improving the general knowledge level and professional level. However, there is a phenomenon that, although learners use these mobile learning applications for some time, they might stop utilising or even reject continuing to utilise them (Nie et al., 2020).

Some research evaluated the effectiveness of m-learning applications (Li and Hegelheimer, 2013; Chen, 2018) and the variables affecting learners' initial adoption and acceptance (Nie et al., 2020; Bian and Liu, 2017); however, few studies focused on continuous use (Wang and Yu, 2024). Additionally, the investigation of users' intentions towards utilising m-learning applications is considered a reliable indication of m-learning applications. Thus, greater intention is focused on assessing the continuous intention to utilise among users (Amir et al., 2020).

Several models and theories applied in previous studies focused on analysing the ongoing intention to accept technologies among users, such as UTAUT, TAM, TPB and ECM (Ding, 2019; Prasetya et al., 2021). However, assessing users' determination in the post-adoption phase requires focused attention research (Sayyah Gilani et al., 2017). The ECM is considered one of the most popular frameworks used to assess continuous intention in the IS field, as it is established to assess the phase of post-adoption instead of the first acceptance and adoption phase (Steuer, 1995; Rabaa'I et al., 2021; Cheng, 2020).

According to Guo et al. (2023) and Bhattacherjee (2001), in the ECM, users' PU and confirmation affect their satisfaction, which in turn influences users' continuous intention. However, other factors could play a role in and affect students' continuous intentions. Students' self-regulation focused on their behaviour to monitor and control the learning process, which enabled them to reach their educational goals. To our knowledge, the combined ECM with self-regulation to assess their influences on the continuous intention to utilise mobile learning applications has not been examined. Thus, this study proposes a model by extending the ECM and combining self-regulation to assess students' continuous intentions to utilise m-learning applications.

The ECM

The ECM was established by Bhattacherjee (2001) and drawn from expectation confirmation theory, which is widely utilised for understanding consumer behaviour post-purchase. The ECM is seen as a more solid and rigorous model for assessing continuous intention to accept technologies than other well-known models, such as the TAM and UTAU (Ambalov, 2018). Figure 1 shows ECM model.

According to the ECM, PU and confirmation affect satisfaction and both PU and satisfaction affects the continuous intention to use a given IS technology (Bhattacherjee, 2001).

PU, confirmation, satisfaction and continuous intention

PU refers to users' evaluations of the advantages using IS technology, especially when it improves performance and outcomes (Scherer et al., 2019). It is a predicting key for technology adoption since it not only predicts continuous intention but also predicts satisfaction, which plays a mediating role in affecting continuous intention (Bhattacherjee, 2001). On the other hand, confirmation refers to users' perceptions and expectations regarding the use of IS systems (Alshammari and Alshammari, 2024). Confirmation was a key factor that determined students' satisfaction with IS technology (Alshammari and Alshammari, 2024; Stone and Baker-Eveleth, 2013; Limayem and Cheung, 2008).

Satisfaction is users' assessment of their use experiences with IS systems (Alshammari and Alshammari, 2024; Bhattacherjee, 2001). It predicts the continuous intention to utilise a specific technology (Choi et al., 2019; Mouakket, 2015; Alshammari and Alshammari, 2024). Satisfied users with utilising a system are likelier to continue utilising it (Ashfaq et al., 2020; Alshammari and Alshammari, 2024). Few studies were conducted to assess the effect of satisfaction on continuous intention (Ifinedo, 2007; Ramadhan et al., 2022; Alshammari and Alshammari, 2024).

Based on this, the following hypotheses were formulated:

> *H1*: Confirmation positively affects satisfaction.
>
> *H2*: PU positively affects satisfaction.
>
> *H3*: PU positively affects the continuous intention to utilise m-learning applications.
>
> *H4*: Satisfaction positively affects the continuous intention to utilise m-learning applications.

Self-regulated learning

SRL refers to controlling students' motivations, learning behaviors and thoughts to accomplish and achieve their learning objectives (Pintrich, 1995; Boekaerts et al., 1999). It deals with how students use cognitive and metacognitive learning approaches and strategies which are controlled by motivation (Pintrich and Schragben, 2012).

Hashim et al. (2015) found that when students had high self-motivation in blended online courses, this led to a more positive attitude towards using it. Several scholars have found that motivation influences students' behavioral intention to study in online courses, based on self-determination theory (Zhou, 2016; Ifinedo, 2017; Joo et al., 2018). Thus, the following is hypothesised:

> *H5*: Students' SRL positively affects their PU.

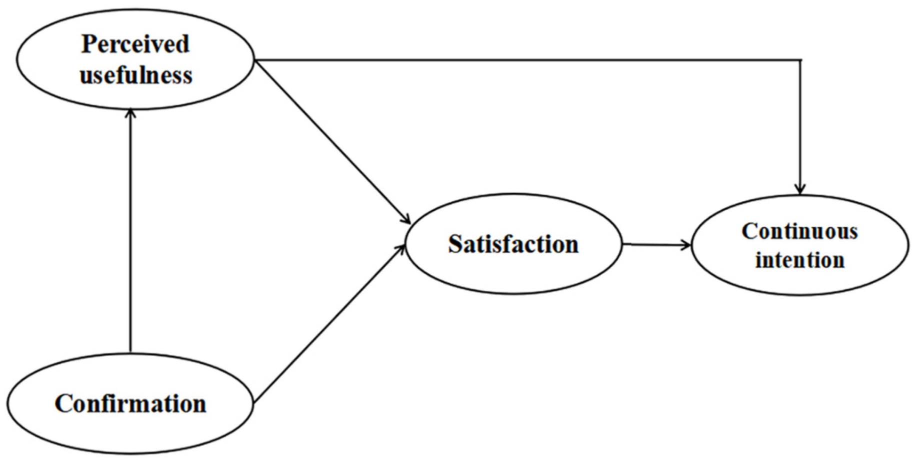

FIGURE 1
ECM model (Bhattacherjee, 2001).

H6: Students' SRL positively affects their confirmation.

The proposed research model is presented in Figure 2.

Methodology

Research design

A quantitative research design was utilized to determine measurement metrics for analyzing relationships among variables and testing theoretical models through statistical analysis (Creswell and Creswell, 2017). Educational and behavioral research designs that are quantitative are most effective in creating generalizable insights and understanding how user behavior evolves in technology enhanced learning environments (Gall et al., 2007).

Participants

To gather data from respondents, Google forms (and URL links) were delivered via email to the targeted population during the first semester of 2024. A total of 227 students participated in filling out the questionnaires. A simple random technique was employed to select the samples to ensure that all samples were representative of the study participants. In order to have the students' responses be relevant, they were targeted to be students who have had prior experience using m learning applications. Thus, all participating students had experience using m-learning applications. They filled out the questionnaires voluntarily and anonymously, as there was no information that directly led to the respondents' personal information. All items were measured using a 5-point Likert scale.

Most of the respondents were female students (135; 59.5%) and 92 (40.5%) were male students. In terms of their years of study, most of the participants were enrolled in the first year (64: 28.2%), followed by those in the second year (55: 24.2%) and third year (46: 20.3%), while the lowest were enrolled in the fourth year (26: 11.5%). In terms of their educational level, most of them were enrolled in a bachelor's degree programme (136: 59.9%), followed by those enrolled in a diploma programme (82: 36.1%), while the lowest were enrolled in a master's degree programme (9: 4.0%). Regarding their colleges, most of them were enrolled in Applied College (81: 35.7%) followed by college of Education (31: 13.7%) and college of Business Administration (25: 11.0), while the lowest were enrolled in the preparation year (6: 2.6%). Regarding the m-learning applications they were using, most used the Blackboard application (221: 97.4%), followed by ChatGPT (5: 2.2%) and Coursera (1: 0.4%). Table 1 shows demographic information of respondents.

Instrumentation

The first part of the survey was specified for the respondent's demographic information, which was self-created and included five questions regarding their gender, years of study, education level, college and most used m-learning applications, while the second part has 18 items to measure model's five constructs (i.e., confirmation, PU, satisfaction and continuous intention), adapted from Bhattacherjee (2001) and Mouakket (2015), while the items measuring students' self-regulation were adapted from Gökçearslan et al.'s (2016) study.

Due to the questionnaire being translated into Arabic, a "back-translation" was applied. Two bilingual experts (English and Arabic) were asked to translate the questionnaire, which was originally in English to Arabic, to maintain the equivalence of the translation. To

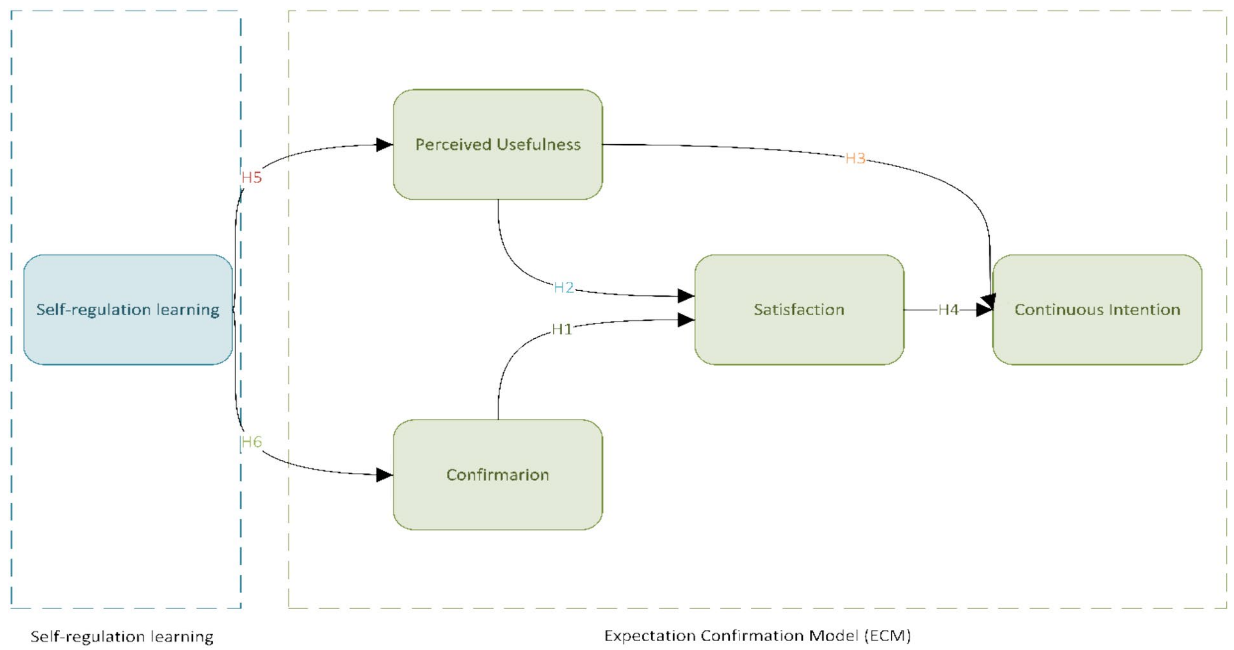

FIGURE 2
Proposed research model.

TABLE 1 Demographic information.

		Frequency	Percent
Gender	Male	92	40.5
	Female	135	59.5
Years	First	64	28.2
	Second	55	24.2
	Third	46	20.3
	Fourth	26	11.5
	Fifth	36	15.9
Level	Diploma	82	36.1
	Bachelor	136	59.9
	Master	9	4.0
Colleges	Applied college	81	35.7
	Education	31	13.7
	Sharia and law	21	9.3
	Computer science and engineering	18	7.9
	Science	10	4.4
	Preparatory year	6	2.6
	Business administration	25	11.0
	Arts	24	10.6
	Pharmacy	11	4.8
M-learning application used	Blackboard	221	97.4
	ChatGPT	5	2.2
	Coursera	1	0.4
	Total	227	100.0

ensure face and content validity, five professors were invited to check and comment on the instrument's length, format and the scales' correct wordings. Some of these items, due to their recommendations, were revised to better match the research objectives. The pre-test results showed that face and content validity were achieved.

Data analysis

For analysing the demographic information of the respondents, SPSS (Version 24.0) was used. To analyse the relationships of constructs, two steps in structural equation modelling (SEM) AMOS were used. Confirmatory factor analysis (CFA) was conducted to assess constructs' validities. Then, SEM was applied to assess the constructs' relationships and hypotheses.

Results

Confirmatory factor analysis

CFA is an analysis approach conducted to validate the measurement model concerning the handling of correlations, measurement errors and validities. According to Awang (2015), all validities must be checked during a CFA before moving to the second step to assess the relationships and test the hypothesis in SEM. Construct validity was met when all indices of the model met the recommended values suggested in the literature (Awang, 2015). Thus, the CFA was run after deleting one item (PU3) due to its low loading factor. The values of the indices in the model are shown as the output of CFA in Figure 3.

As shown in the above figure of the CFA output, all indices of the model met the required values in the literature "Chisq/df = 2.356 < 3.0; CFI = 0.965 > 0.90; TLI = 0.954 > 0.90; IFI = 0.965 > 0.90; RMSEA = 0.077 < 0.08." Thus, construct validity was achieved (Hair et al., 2010; Awang, 2015).

Next, convergent validity is achieved once the composite reliability (CR) value is greater than (0.6) and average variance extracted (AVE) is greater than (0.5) (Hair et al., 2010). The output of these values, as shown in Table 2, confirms that the suggested values are met and, thus, convergent validity is achieved.

Lastly, discriminant validity is essential to ensure that each construct is distinct from other constructs. According to Awang (2015), discriminant validity is met once all values of the square root of AVE, which are in bold, are greater than all other values in its rasa bd column. As shown in Table 3, all bolded values met the suggested recommendations. Thus, discriminant validity was achieved.

Standardised estimate

A standardised estimate is necessary to measure the rigour and strength of relationships between constructs, factor loading and the R square of the dependent variable. The standardised estimate output is run and is presented in Figure 4.

The R square of the dependent variable in the model is 0.79, confirming that 79% of students' continuous intention to use m-learning applications is explained by all other factors, namely satisfaction, PU, confirmation and self-regulation. According to Cohen (1988), the values of R square above 0.26 confirm the high explanatory power of the proposed mode. Thus, the proposed model is a robust model for explaining the phenomena of the factors that affect the utilisation of m-learning applications.

Unstandardised estimate

An unstandardised estimate run is needed to calculate the beta weight and critical ratio to test the hypothesis of this research. Thus, the unstandardised estimate is run, and its output is shown in Figure 5.

Hypotheses testing results

The results confirm that self-regulation had a positive significant effect on both PU and confirmation "$\beta = 0.806$, $p < 0.05$; $\beta = 0.968$, $p < 0.05$." Thus, H5 and H6 are supported. Furthermore, confirmation had a positive significant effect on satisfaction "$\beta = 0.940$, $p < 0.05$." Thus, H1 is supported. Also, PU positively affected the continuous intention "$\beta = 0.297$, $p < 0.05$." Thus, H3 is supported. Furthermore, satisfaction had a significant positive effect on continuous intention "$\beta = 0.638$, $p < 0.05$." Thus, H4 is supported.

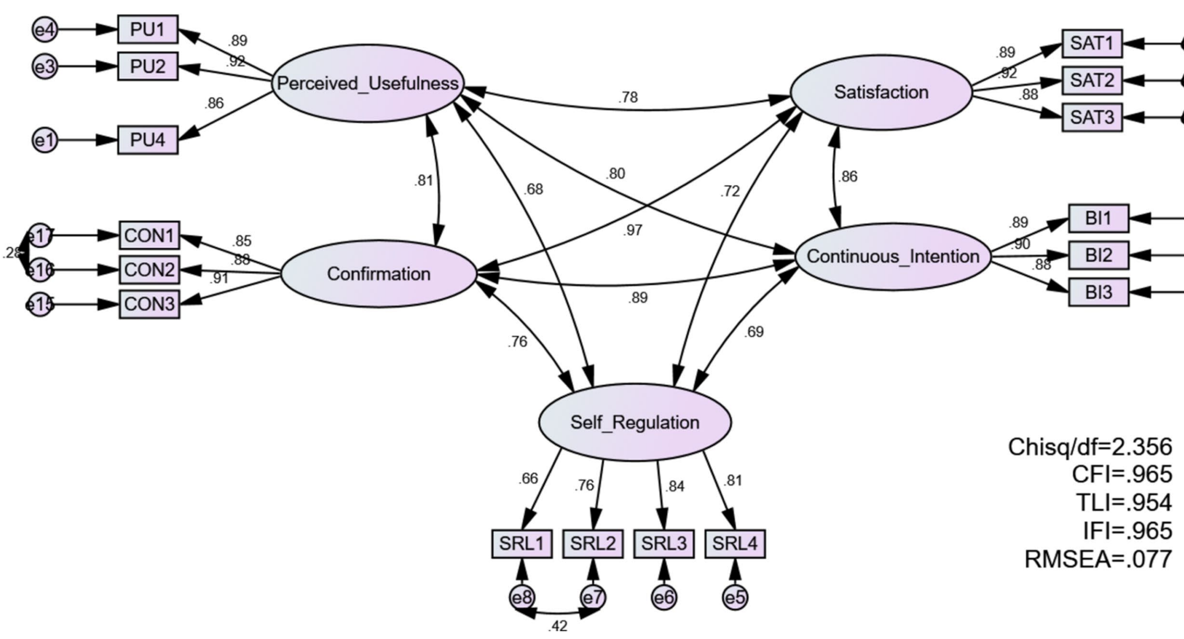

FIGURE 3
CFA output.

TABLE 2 CR and AVE values.

	CR	AVE
Satisfaction	0.925	0.804
Perceived_Usefulness	0.920	0.794
Self_Regulation	0.855	0.598
Continuous_Intention	0.920	0.793
Confirmation	0.911	0.773

However, PU had an insignificant effect on satisfaction “$\beta = 0.098$, $p > 0.05$.” Thus, H2 was rejected. Table 4 presents the hypothesis results.

Discussion

This study assessed students’ continuous intention to use m-learning applications by combining ECM and SRL. The research model was proposed and the data of 227 respondents were collected and analysed using two steps in SEM AMOS. A detailed discussion is presented in the following sections.

The findings showed that PU and satisfaction directly affected the continuous intention to use m-learning applications, which confirms previous studies (Ambalov, 2018; Alshammari and Alshammari, 2024). These findings indicate that when students perceive using m-learning applications as useful and are satisfied with using them, this will lead to a continuous intention to use them. However, PU had an insignificant effect on satisfaction. These findings might explain why when students perceive the use of m-learning applications as useful, this does not necessarily make them feel satisfied with using such applications.

Furthermore, confirmation positively affected satisfaction, which confirms previous studies (Bhattacherjee, 2001; Alshammari and Alshammari, 2024). These findings indicate that when students had great experience with using m-learning applications, this would positively affect their satisfaction. In other words, when students confirm their positive experience and when these m-learning applications meet their expectations, they are likelier to be more satisfied with using these m-learning applications.

Additionally, SRL had a significant positive indirect effect on the continuous intention to use m-learning applications and a direct effect on both PU and confirmation. These findings are consistent with some prior studies (Hood, 2013; Lee, 2010). The findings might indicate that when students have a higher level of SRL, they are likelier to perceive m-learning applications as useful and confirm their positive experience, which leads to continuous use. Hood (2013) found that greater reliance on rehearsal, high work commitments and high critical thinking and self-regulation were core variables that predicted students’ continuous intention to utilise online lecturers.

Contributions and implications

This study has some main contributions. First, this is the first study to explore the role of SRL by combining it with the ECM model to investigate students’ continuous intention to use m-learning applications. It provides a theoretical framework which enhances the understanding of the phenomenon of the continuous use of m-learning applications and could be utilised as a basis for future studies.

Second, assessing the effects of self-regulation, PU, confirmation and satisfaction on the continuous intention to use m-learning

TABLE 3 Discriminant validity index.

	Satisfaction	Perceived_ Usefulness	Self_Regulation	Continuous_ Intention	Confirmation
Satisfaction	0.987				
Perceived_Usefulness	0.779	0.891			
Self_Regulation	0.716	0.679	0.773		
Continuous_Intention	0.865	0.797	0.688	0.891	
Confirmation	0.974	0.810	0.764	0.889	0.979

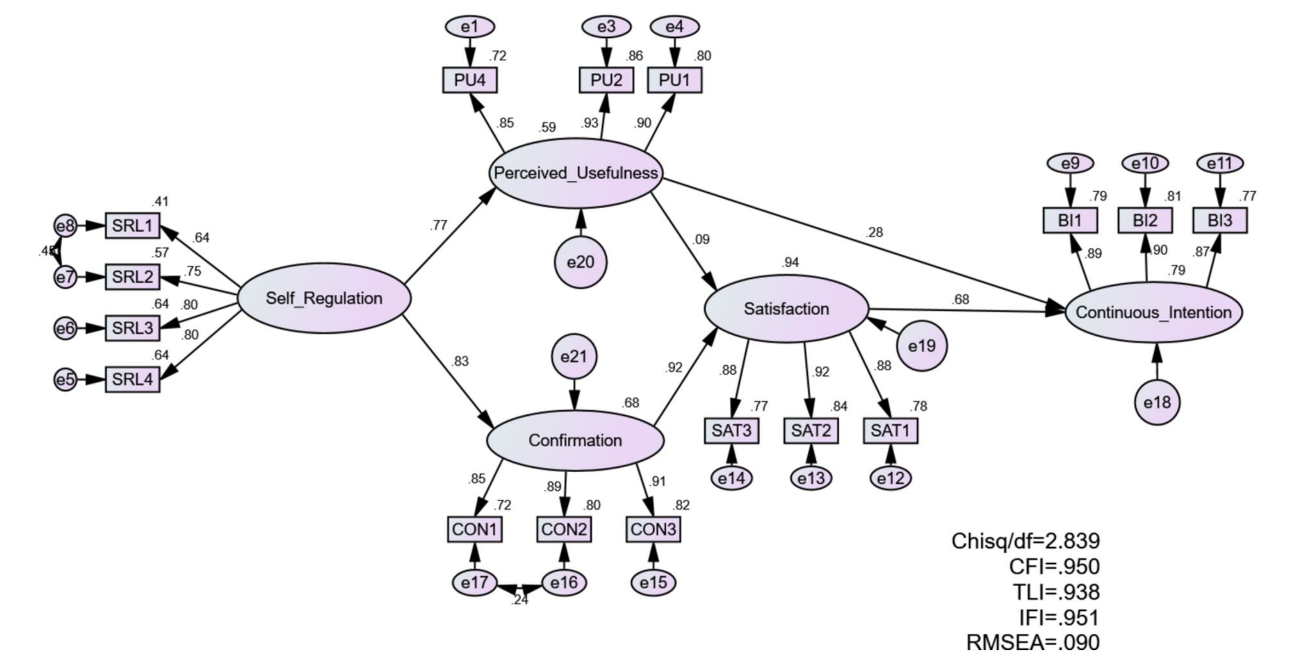

FIGURE 4
Standardised estimate output.

applications assists in bridging the existing research gap in the literature on ECM and adoption of technologies. Another notable contribution is that the proposed model has a high explanatory power (R2 = 0.79 (79%)) when compared to the original proposed model by Bhattacherjee (2001), which explained 41%. This indicates that all constructs in the model, including the additional construct, SRL, played a significant role in explaining the phenomena of utilising m-learning applications.

The findings have practical implications for designers and practitioners of m-learning applications. The positive effect of both PU and satisfaction, which influenced the continuous intention to utilise m-learning applications, suggests that the designers of m-learning applications should pay attention to providing learners with useful content and materials and a pleasant environment. M-learning application developers could enhance PU and satisfaction by working on improving app-loading speeds, minimising response times and providing the materials that students would like to use for learning.

Confirmation affected students' satisfaction. Thus, developers and instructors should ensure that students have positive experiences using m-learning applications. This could be done by considering students' opinions regarding their use of m-learning applications and by finding out if they have any difficulties with their use that need to be solved. Doing this could lead to students being satisfied with using m-learning applications.

Furthermore, SRL affected both PU and confirmation. Thus, instructors should pay attention to enhancing students' motivation through and to their learning behavior when using m-learning applications. When students have self-regulation and motivation, it could lead them to perceive these applications as useful and confirm their positive experiences with using them, which could lead to their continuous use.

Limitations and future research

Although this study has promising findings, there are some limitations. The study sample size is limited to one university in Saudi Arabia, which might affect the findings' generalizability. Thus, future studies might include samples from other universities or from other contexts. Furthermore, this study focused on a quantitative method using questionnaires. Future studies could use a

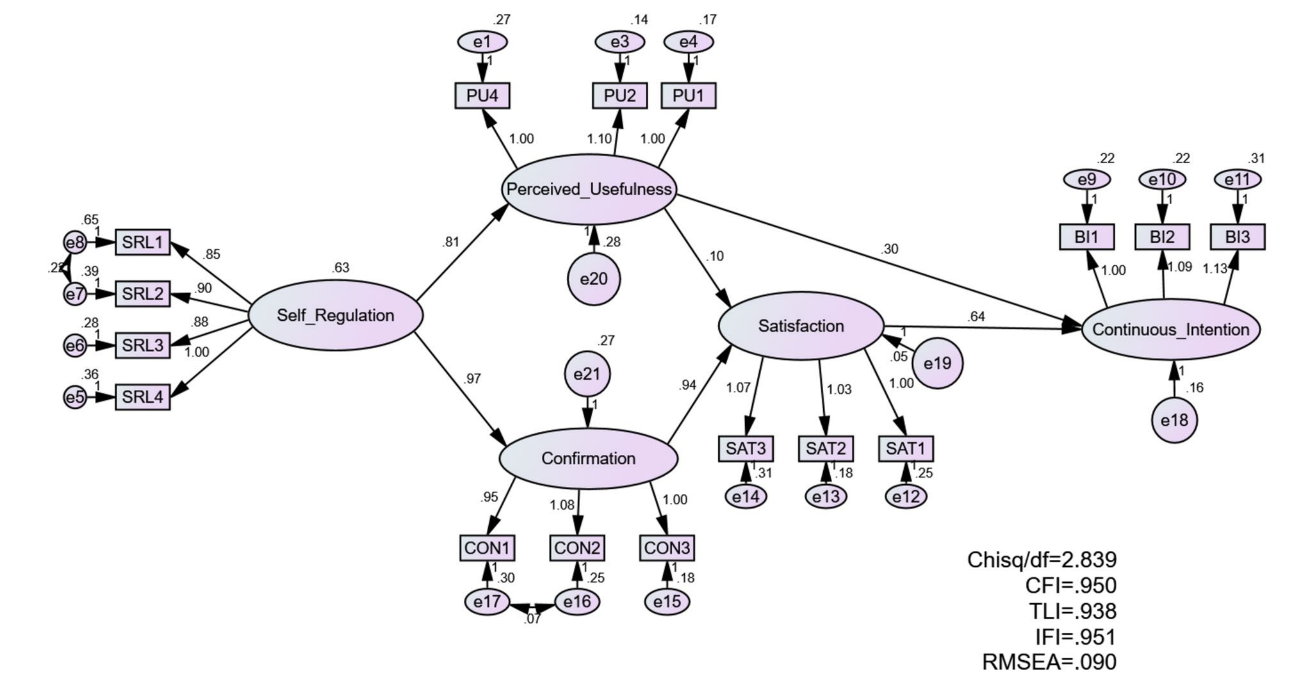

FIGURE 5
Unstandardised estimates.

TABLE 4 Hypothesis results.

	Estimate	S.E.	CR	*P*	Results
Self_Regulation ➔ Confirmation	0.968	0.080	12.028	***	Supported
Self_Regulation ➔ Perceived_Usefulness	0.806	0.077	10.520	***	Supported
Confirmation ➔ Satisfaction	0.940	0.060	15.583	***	Supported
Perceived_Usefulness ➔ Satisfaction	0.098	0.051	1.897	0.058	Not Supported
Perceived_Usefulness ➔ Continuous_Intention	0.297	0.063	4.739	***	Supported
Satisfaction ➔ Continuous_Intention	0.638	0.059	10.726	***	Supported

mixed-methods, which might provide deeper understanding regarding the phenomenon of the continuous use of m-learning applications. This study extended the ECM and included the SRL construct. Future studies might extend ECM and incorporate other factors which may affect the continuous intention of m-learning, such as instructor support and engagement.

Conclusion

This combines ECM with SRL to assess factors which affect students' continuous intention to utilise m-learning applications. The findings showed that SRL had an indirect effect on students' continuous intentions and a direct effect on both confirmation and PU. Furthermore, both PU and satisfaction affected students' continuous intention to use m-learning applications. Thus, designers and developers of m-learning applications should consider these factors when designing m-learning applications because they directly or indirectly affect the continuous intention to utilise m-learning applications.

Furthermore, educational institutions and instructors should work on improving SRL among students by increasing their motivation, as a higher level of students' SRL would positively affect their perception of m-learning applications as useful and lead to perceiving a positive experience that can be confirmed by them. Considering all of this could lead to the continuous intention to use m-learning applications.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Ethics statement

The studies involving humans were approved by Ethical approval committee at University of Ha'il. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

SuA: Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. SaA: Formal analysis, Funding acquisition, Project administration, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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