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The Role of Self-Regulated Learning in Shaping Students' Intention to Use E-Learning Systems

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Abstract

The widespread use of e-learning systems in higher education highlights the necessity to understand the determinants of students' intention to utilize e-learning systems. This study builds upon the Expectation–Confirmation Model (ECM) by incorporating self-regulated learning (SRL) as a pivotal construct to underpin students' intention to utilize e-learning systems. Specifically, this study explores the influence of perceived usefulness (PU) and confirmation on SRL, and the influence of SRL on behavioral intention (BI). Data were obtained by utilizing an on-line questionnaire sent to university students, with a total of 214 valid responses. Descriptive statistics were calculated in SPSS, while AMOS was employed for structural equation modeling (SEM), following a two-step approach combining confirmatory factor analysis (CFA) and path analysis. Findings revealed that both PU and confirmation exerted significant and positive influences upon SRL, with confirmation showing a stronger effect. In addition, SRL had a strong positive effect on BI, highlighting its central role for predicting students' intention to use e-learning systems. Findings extend the original ECM and confirm the role of SRL as both an outcome of system-related perceptions and a significant predictor of continued use of technology. The practical implications for educators and system designers in stimulating SRL via educational e-learning environments are also considered in the discussion section.

Introduction

The emergence of epidemics, most notably the COVID-19 pandemic, has impacted education significantly across the world. To reduce learning disruptions, many countries employed e-learning systems as an alternative approach of delivering instruction in universities (Alshammari & Alkhwaldi, 2025). The effectiveness of these systems, however, depends significantly on students' acceptance to adopt these alternative e-learning systems (Alyoussef, 2023). Several theoretical models have been used to explain students' acceptance, whereby the Technology Acceptance Model (TAM) has been positioned amongst the most widely referred to and researched models. Specifically, TAM has adopted an emphasis on some important factors like perceived usefulness (PU) that shape students' intention to utilize alternative e-learning (Almulla, 2021). Other important determinants of social influence and effort expectancy have also been shown to have a significant impact on students' behavioral intention to adopt e-learning systems (Bessadok, 2022).

Research indicates that although initial acceptance of e-learning systems is critical, and acceptance is valuable in determining educational effectiveness, the actual continued use of e-learning systems is more important (Al-Adwan et al., 2022). To assess this dimension of continued use, ECM has been utilized widely to examine students' continuance intention of using e-learning. In the ECM, the constructs such as satisfaction, confirmation, and PU are the main predictors of continuance intention. Each construct of the ECM is shown to be valid in a growing body of information systems research (Huang & Zhi, 2023; Alshammari & Alshammari, 2024). Beyond the system-related constructs of the ECM, there are learner-centered constructs, such as self-regulated learning (SRL), that can evaluate students' continuance intention to utilize e-learning systems. Consequently, exploring both dimensions (system-related constructs and learner-centered constructs) should be accounted for when studying broader dimensions of long-term adoption. Moreover, e-learning systems have continued to represent an increasingly powerful opportunity for students and have established a significant degree of flexibility, adaptability, and scalability, allowing for non-physical, geographical or situational constraints to facilitate continued education (Alenezi, 2023). This is also supported by e-learning global market statistics growing to approximately USD 288.8 billion in 2022 to an estimated USD 840.11 billion in 2030. This represents a compound annual growth rate of 17.5% from 2021 to 2030 (Bagdi et al., 2023). The growth of e-learning is also expected to accelerate significantly within e-learning market in Saudi Arabia. Furthermore, SPER Market research (2023) projects that the Saudi Arabian e-learning market will reach an estimated USD 8.44 billion by 2032 (a CAGR) of 16.32%, indicating significant momentum and the role of e-learning in the Kingdom. The broader trends reflect the increasing relevance of e-learning, both in a global and regional educational system. Although overall financial investments in education remain substantial, particularly in Saudi Arabia, many educational institutions continue to experience difficulty realizing the potential of e-learning (Aldraiweesh & Alturki, 2023). What may potentially add to these challenges were the abrupt and extreme changes to remote education at the commencement of the COVID-19 pandemic, where educators and students were displaced from any semblance of the traditional and norm in face-to-face or on-campus delivery. These rapid changes and dislocations likely resulted in dissatisfaction for learners who were used to being face-to-face (Tulaskar & Turunen, 2022). What likely compounded these challenges were students' none-conducive home environments, uncertainty with online education quality, and lack of in-person social interaction which further continued to obscure their experience with e-learning (Soubra et al., 2022).

In light of student engagement diminishing and increasing sustainable use, researchers highlight the need for redesigning learning spaces, adapting technology, and improving the ultimate online learning experience. Therefore, the e-learning systems being depended on are reliant on a full evaluation of a number of dimensions, such as SRL. According to studies by Alshammari and Alkhabra (2025), SRL had an indirect influence on behavioral intention (BI) through PU, confirmation, and satisfaction by being mediating constructs in m-learning platforms. The objective of this study is to examine the direct effects of SRL on student behavioral intention to utilize e-learning systems, the influences of PU and confirmation of SRL which provides a more holistic understanding of continuance intention. SRL is a constructive process involving students that monitor their learning progress, set goals for their learning, and regulate their cognition, behaviors, and motivation (Pintrich, 2004). It empowers learners with the ability to have control over the strategies that they will employ in order to develop meaningful academic outcomes (Hamdan et al., 2021). Even if students have low intrinsic interest regarding the content knowledge, SRL allows them to remain engaged through motivational strategies and exert more effort in their studies. A variety of processes involved in self-planning, self-organization, self-monitoring, self-evaluation, and self-control provide learners with a manner to engage with how their own educational experiences are constructed which led to increase the effectiveness of their learning experiences (Anthonysamy et al., 2020). Several well-conducted studies have established SRL as a necessary trait for student success (Mäenpää et al., 2018; Vanslambrouck et al., 2019). As already established, SRL has a vital importance to having a sustained learning experience, thus it must be investigated in regards to its direct effects toward students' intention to utilize e-learning. Consequently, in this study we extend ECM in order to explain the direct effects of SRL toward predictive behavioral intentions as well as PU and confirmation as contributing influences of SRL. It will offer a more holistic model into exploring students' continuance intention toward e-learning.

Even though there is an evidence base for SRL as a variable, it has not gained sufficient attention from researchers that have examined the relationship of SRL and behavioral intentions (BI) with respect to using e-learning systems. For instance, past research has explored self-regulated learners' within various contexts such as schools (Molenaar et al., 2020), higher education (Azevedo et al., 2005), and MOOCs (Wong et al., 2019), but not enough research has been conducted on SRL examining it as an independent construct to examine students' behavioral intentions (BI) to use e-learning systems. Moreover, little attention was given toward the potential roles of PU and confirmation on SRL, which is an important consideration given the critical role SRL plays to achieve persistence and effectiveness working in a technology-supported learning environment. Therefore, this study aims to extend ECM to examine the relationships between PU and confirmation on SRL, as well as a direct relationship from SRL on students' BI, to form a better explanation of their sustained intention in an active digital-learning environment.

While the original version of the ECM (Bhattacherjee, 2001) offered satisfaction as the main intervening variable to the relationship between confirmation, PU and intention, this study adapts the ECM for the e-learning environment and considers SRL and removes satisfaction from the model. This study has two primary reasons for the change. First, because SRL is more central than satisfaction in explaining students' persistence, motivation, and engagement to self-directed digital learning environments, SRL measures were oriented toward describing their planning, monitoring, and control of their learning behaviors (Pintrich, 2004; Gökçearslan et al., 2016). Second, previous research indicates ECM is dynamic, not a static model; in other words, the ECM has been adapted or extended in other areas, including mobile learning, MOOCs, and e-government by adding new constructs or new paths (Alshammari & Alshammari, 2024; Buabeng-Andoh, 2025; Jung & Jo, 2025; Alshammari & Alkhabra, 2025). Following the theme of extending the model, this research will examine the PU and confirmation influences toward SRL and examine the direct influence of SRL with respect to students' BI to utilize e-learning systems in order to enhance a full understanding of continuance intention in an environment whereby learners' self-regulation is important to their success.

Literature Review

With the rapidly growing technologies and the impact of internet accessibility, e-learning systems have taken a fundamental place in today's education (Balaman & Baş, 2023). E-learning can be broadly defined as a form of teaching and learning facilitated by electronic devices and digital media (Clark & Mayer, 2023). E-learning systems may include a variety of modes of delivery which could include a combination of learning management systems (LMSs), webinars, online courses, podcasts, virtual classrooms and video conferencing which let learners explore different modes of knowledge acquisition. One major benefit of an e-learning system is the flexibility, convenience and cost of education for students and instructors (Rajab et al., 2024). E-learning systems are intended to be more than just content delivery, e-learning systems encompass information systems that allow learners to sign-up for courses, access content, and engage in scheduled learning activities in a secure environment. Furthermore, they can often acts as online training marketplaces allowing learners to search for courses, enroll in courses and pay for courses within the LMS (Waks, 2018).

Alternatively, e-learning systems can be described as an amalgamated interactive service which is not bound by time and space (Klašnja-Milićević et al., 2016). E-learning systems pass on to learners and educators an array of resources and collaborative tools, housed in a repository format, which allow them to potentially modify the educational processes (Haleem et al., 2022). In addition to providing access to instructional processes, e-learning systems give learners the means to engage in a variety of interactive and collaborative learning activities. E-learning systems can also develop online communities of practice where learners can share knowledge, investigate ideas, and collaborate on the emergence of solutions to problems, providing learning experiences for individuals and groups (Arumugam et al., 2024). For example, Blackboard is one of the most commonly employed platforms in universities around the world. It is a well-known platform with various tools that assist in teaching and learning such as course management, communication, and assessment (Alzahrani & Alhalafawy, 2023). In addition, there has been a growing interest in a new product type of an e-learning system known as MOOCs. A MOOC is often seen as an open-access online course created by an educational organization or institution; MOOCs also offer interactive components that may include video lectures, forums to discuss ideas, and quizzes that require engagement from learners to assist them engage in the process of learning. With the potential for MOOCs to widen access to quality education, they have proven to have high dropout rates and have limited options to accrue credit for completion, inhibiting their effectiveness (Virani et al., 2023).

As technology rapidly develops alongside ongoing changes to educational practice and policy, we are experiencing a shift in how e-learning platforms are designed and delivered. With changes in technology and infrastructure supporting digital learning, it is expected that e-learning could play an increasingly pivotal role in the future of our education system. As such, we must continue to conduct research about e-learning systems and services, examining both the benefits and limitations they may present to learners so as to ensure that education is effective and equitable while we adapt to constant change. However, the success (and ultimately sustainability) of e-learning and services is reliant on the degree to which students adopt those systems. Recent literature shows that it is imperative to understand the determinants that influence students' intention to utilize e-learning systems, because the full potential and benefits of these systems for students can be achieved only when they are adopted (Alshammari & Alkhabra, 2025; Alshammari & Alkhwaldi, 2025; Shaikh et al., 2025). Therefore, we need to understand how to measure and assess the determinants of students' intention to accept e-learning, so as to maximize the transformative effects of e-learning.

ECM

Bhattacherjee (2001) applied Expectation–Confirmation Theory (ECT) and TAM to develop the ECM in the sphere of information systems. The ECM postulates that users' continuance intention of using has three influences: confirmation, PU and satisfaction. More specifically, confirmation of prior use of the system and PU after adoption affect users' continuance intention to utilize the system, while satisfaction acts as a mediator between confirmation of prior use, PU, and continuance intention. In the time since it has developed, ECM has been adopted and modified by several authors, whereby many have merged ECM with other theoretical models, or included external variables, to explain users' behavioral intention to continue using information systems. Given the growing importance of learner-centered constructs within digital education, extending ECM to include SRL is a timely and worthwhile extension that may enhance our understanding of students' intention in e-learning environments. The ECM model is presented in the attached Figure 1.

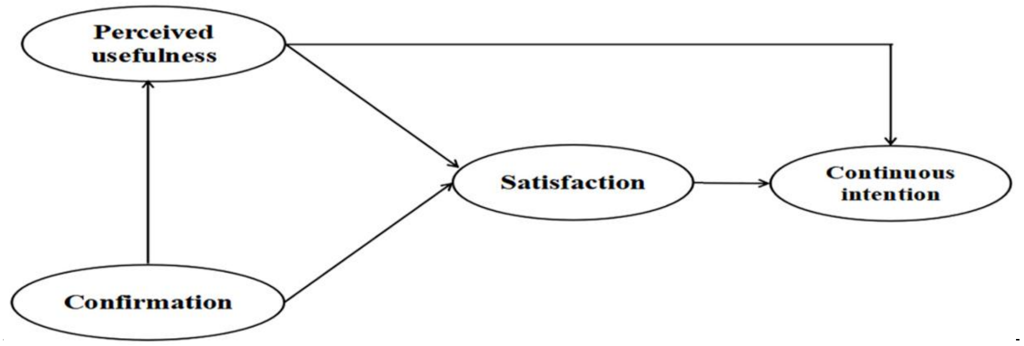

Figure 1. ECM Model. Note. Adapted from Bhattacherjee (2001)

Hypotheses

PU

The perception of PU of e-learning is broadly recognized as an important antecedent of learners' engagement and adoption behaviors. PU refers to the level of belief students have that using an e-learning system will improve their academic performance and learning experience (Ismail et al., 2020). When learners perceive a system as useful, they are more likely to be motivated to use it actively, adopt it into their study practices, and reference it as a source to achieve their learning goals. PU is shaped by how well the system meets students' expectations, delivers fast access to learning resources, and fulfills academic needs. Within the scope of e-learning, PU influences not only satisfaction and intention, but also potentially SRL as students are more likely to plan, monitor, and evaluate their learning when they perceive direct benefits from the system. Given this rationale, the study presents the following hypothesis:

H1. PU positively affects SRL in e-learning systems.

Confirmation

Confirmation represents the degree to which students' actual experiences with an e-learning system do or do not match their pre-existing expectations. When learners initially have positive experience and confirm expectations, the learners rate the experience further positively, reinforcing their perception of effectiveness and trust of the e-learning system (Nikou, 2021). This positive outcome enhances their initial feelings of trust, providing a motivational boost to continue with the e-learning system. Past studies have shown evidence that confirmation has a strong influence on users' satisfaction with technology-based systems (Muñoz-Carril et al., 2021). The effect of confirmation is important in e-learning because learners are relying on a system whether they are working in a group or independently; this requires a great deal of trust. The possibility of confirmation is enhanced in e-learning systems when the learner feels it meets or exceeds while supporting reliability in resource access, interactivity in learning and value towards their overall academic goals. When students experience confirmation through access to resources, they are more likely to engage in active learning. Active learning allows students to take the role of the self-regulating learner, in relation to SRL, when students plan, monitor and manage their own learning, which may also lead to independence. Because of this rationale, the following hypothesis will be provided:

H2. Confirmation positively affects SRL in e-learning systems.

SRL

SRL is accomplished when learners have the ability to plan for the learning task, monitor it, and evaluate their learning, while having control over their motivation, cognition, and behavior (Pintrich, 2004). SRL is especially relevant in e-learning contexts where students are usually in a position of self-managed learning, and the continuous support offered in in-person learning environments is lacking. SRL allows students to set goals, manage time, choose effective strategies for learning, and persevere when learning gets difficult. Research has highlighted the significance of SRL in success, persistence, and engagement in technology usages (Anthonysamy et al., 2020). The more self-regulatory skills students develop, the more they can better maintain their motivation, engage in a more meaningful approach with e-learning, and implement e-learning system usage into their longer-term learning behaviors. Subsequently, this may have an impact to improve their behavioral intention (BI) to continue using e-learning systems. Based on the argument presented above, the following hypothesis is proposed:

H3. SRL positively affects students' behavioral intention.

Figure 2 presents the research model.

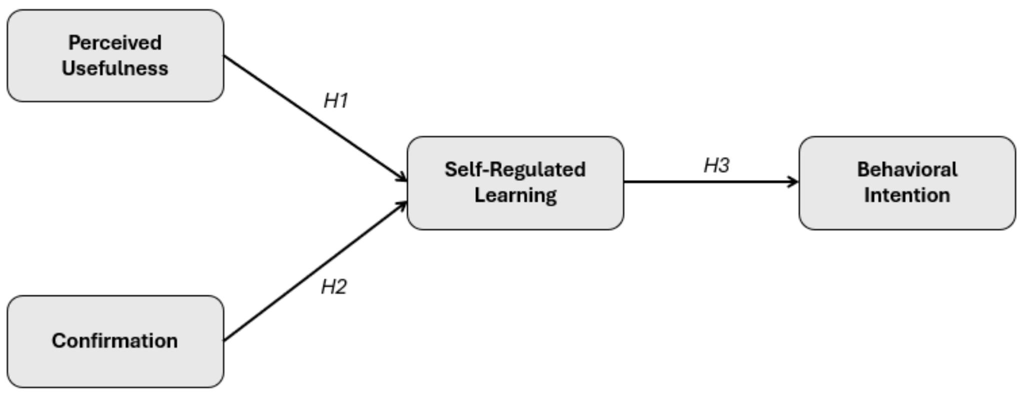

Figure 2. The Research Model

Methodology

Research Design

A quantitative research design is used in this study to examine the proposed hypothesized relationships between perceived PU, confirmation, SRL and BI in the context of an e-learning. A quantitative approach was adopted because it allows researchers to examine causal paths across latent constructs. SEM can assess these causal paths in an empirical way and provides an indication of statistical power (Hair et al., 2019). In technology adoption and e-learning research, researchers have recommended using cross-sectional surveys, which gather data from a single population at a single point in time (Wang & Cheng, 2020). This design permits research to understand all the variables in a connected or related manner efficiently.

Measurement

All constructs were evaluated using items from validated scales adapted from field studies. SRL was measured using items adapted from Gökçearslan et al. (2016), which evaluate how a student is utilizing planning, monitoring, and regulating in an online environment. PU, confirmation and behavioral intention were measured using items adapted from the ECM (Bhattacherjee, 2001). They have five-point Likert scale response options. The wording was only slightly changed to fit into the e-learning context.

Sample and Participants

The target population for this study was university students taking part in e-learning courses. The data were collected via an online questionnaire that was disseminated through Google Forms during the first semester of 2025. After removing incomplete and unusable responses, the final dataset comprised 214 valid responses. The data set was deemed viable to conduct SEM analysis. Hair et al. (2019) recommended a minimum of 150 to 200 cases for medium complexity models while Kline (2016) indicates that a sample size of over 200 cases is optimal to obtain reliable SEM estimates. Thus, the study satisfied the requirement. The study was authorized by the ethical standards committee of the University of Ha'il, which ensured that this study remained compliant with university's institutional ethics in research guidelines.

Data Analysis

Data analysis involved a two-phase process using SPSS and AMOS. In the first phase, SPSS was used for analysis of the demographic information, checking for missing data and outliers, then descriptive statistical analyses. In the second phase, we used a two-step SEM analysis approach in AMOS. In the first step, CFA was conducted to evaluate the measurement model. In the second step, the structural model was tested to examine the hypothesized relationships between PU, confirmation, SRL, and BI. SEM was considered the most suitable analytical approach for this study as it allows for the simultaneous testing of multiple relationships among latent variables, accounts for measurement error, and provides comprehensive model fit evaluation (Awang, 2015).

Results

As illustrated in Table 1, the demographic profile of the 214 respondents demonstrates diverse representation across gender, academic years, study levels, and colleges. In terms of gender, the sample consisted of 40.2% male (n = 86) and 59.8% female (n = 128) participants, indicating a higher proportion of female students. In terms of study level, the majority were bachelor's students (58.9%, n = 126), with 36.9% (n = 79) enrolled in diploma programs and only 4.2% (n = 9) pursuing master's studies. The distribution across colleges highlights the dominance of students from the Applied College (36.4%, n = 78), followed by the College of Education (14.0%, n = 30), Business Administration (10.7%, n = 23), Arts (10.7%, n = 23), Sharia and Law (8.4%, n = 18), Computer Science (7.9%, n = 17), Pharmacy (5.1%, n = 11), Science (4.7%, n = 10), and the Preparatory Year program (1.9%, n = 4). Overall, the demographic data indicate a balanced distribution across academic years and colleges, with a notable predominance of bachelor's-level and female students.

Table 1. Demographic Information of Respondents

Variable	Options	Frequency	Percent
Gender	Male	86	40.2
	Female	128	59.8
Level	Diploma	79	36.9
	Bachelor	126	58.9
	Master	9	4.2
Colleges	Applied College	78	36.4
	Education	30	14.0
	Sharia and Law	18	8.4
	Computer Science	17	7.9
	Science	10	4.7
	Preparatory year	4	1.9
	Business Administration	23	10.7
	Arts	23	10.7
	Pharmacy	11	5.1
	Total	214	100.0

CFA

Pooled CFA has been used to confirm the measurement model as it is thought to be a better option for this purpose than individual CFA. Pooled CFA allows for the simultaneous measurement of several constructs with functions of the correlation among the constructs (Hair et al., 2019; Awang, 2015), all in one construct. It also facilitates management and reduces identification issues that may arise from having few items for a construction (Awang, 2015). With CFA, it is important to establish construct, convergent and discriminant validity (Awang, 2015). Construct validity is represented to be sufficient when the fitness indices fit indices advise that the thresholds recommended by prior research are met (Hair et al., 2019; Awang, 2015). The pooled CFA was in the analysis of this study and the results indicated that the fitness indices achieved the required levels upon removing items with low factor loadings (i.e., PU3) and the covariance of error terms (e10, e11). The final results obtained from the pooled CFA have been included in Figure 3.

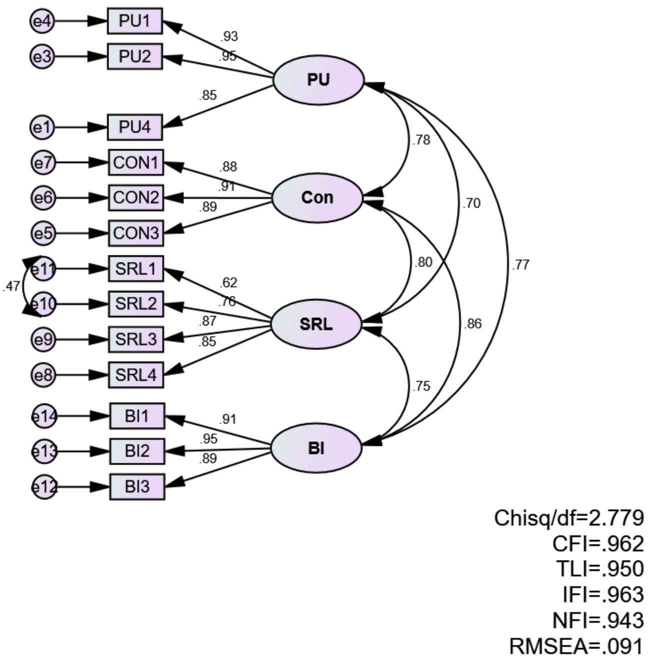

Figure 3. Pooled CFA Output

Awang (2015) stated that the measurement model demonstrates construct validity if it meets acceptable levels of model fit, according to previous recommendations. The model fit indices (see Table 2) demonstrated that the values for all of the model fit indices were acceptable. This shows that the measurement model demonstrated adequate construct validity.

Table 2. Model Fit Indices

Category	Name of index	Index value	Accepted value	Decision	Source
Absolute fit	RMSEA	0.091	<0.1	Achieved	Awang (2015); Hair et al., (2019)
Incremental fit	CFI	0.962	> 0.90	Achieved	
	TLI	0.950	> 0.90	Achieved	
	IFI	0.963	> 0.90	Achieved	
	NFI	0.943			
Parsimonious fit	Chiq/df	2.779	< 3.0	Achieved	

Convergent validity is reached when the AVE for each construct is greater than 0.50 and that the CR is greater than 0.60 (Hair et al., 2019). From Table 3, we can see that the AVE and CR for each construct is above the recommended levels thus confirming convergent validity was achieved.

Table 3. Convergent Validity Results (AVE and CR Values)

	CR	AVE
SRL	0.860	0.609
PU	0.935	0.827
Con	0.923	0.801
BI	0.940	0.840

Lastly, discriminant validity was assessed to show that the constructs in the model were indeed distinct from one another. Discriminant validity is demonstrated in Table 4 as the bold values are the square root of the AVE of each construct, and the non-diagonal values are the correlations among the variables. Discriminant validity is established when the square root of the AVE for each construct (in bold) is greater than the correlation values associated with it, presented in its row and column (Awang, 2015). Using this standard, Table 4 indicates that discriminant validity was achieved.

Table 4. Discriminant Validity

	SRL	PU	Con	BI
SRL	**0.881**			
PU	0.700	**0.910**		
Con	0.805	0.775	**0.895**	
BI	0.748	0.770	0.858	**0.917**

Standardized Estimates

The standardized estimates are used to examine the path coefficients (β) between constructs, the R^2 values, and the factor loadings of the observed items on their respective constructs. In contrast, the unstandardized regression weights, also referred to as beta estimates, are essential for calculating the critical ratio (C.R.), which is used in hypothesis testing. The standardized estimates were analyzed first, and the results are presented in Figure 4.

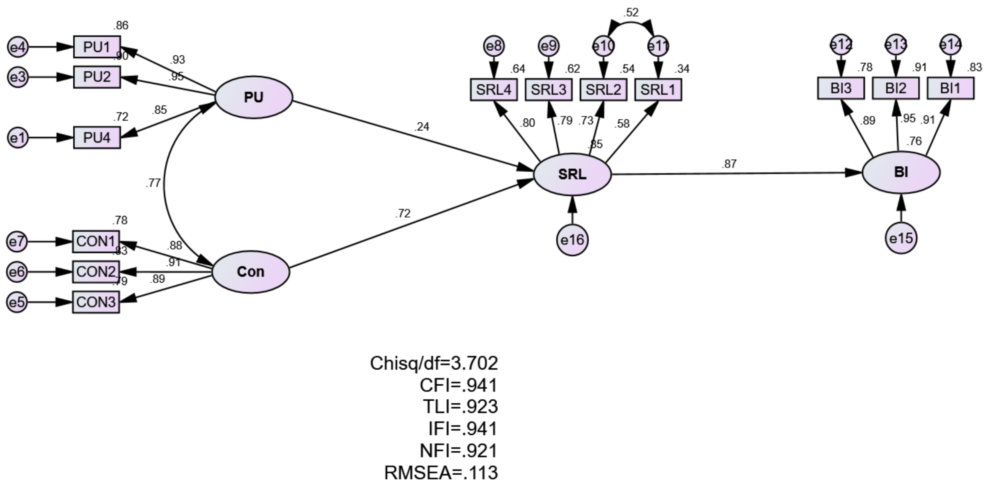

Figure 4. Standardized Estimates

The results reveal that the R² value for behavioral intention (BI) to utilize e-learning is 0.76, suggesting that 76% of the variance in BI is explained by the predictor constructs, namely SRL, PU, and confirmation. This finding demonstrates that the model possesses strong explanatory power in accounting for students' intention to adopt and continue using e-learning platforms. According to Cohen (1988), an R² values above 0.26 indicate high explanatory power. Based on this guideline, the R² value of 0.76 confirms that the model achieves a high level of explanatory power, thereby providing robust evidence of its effectiveness in predicting BI toward e-learning system use.

Unstandardized Estimates

The unstandardized estimates of the model are essential for interpreting the regression weights (β estimates) and for calculating the critical ratio (C.R.), which is used in hypothesis testing. The unstandardized estimates of the model are illustrated in Figure 5, while the detailed regression weights between the constructs are reported in Table 5.

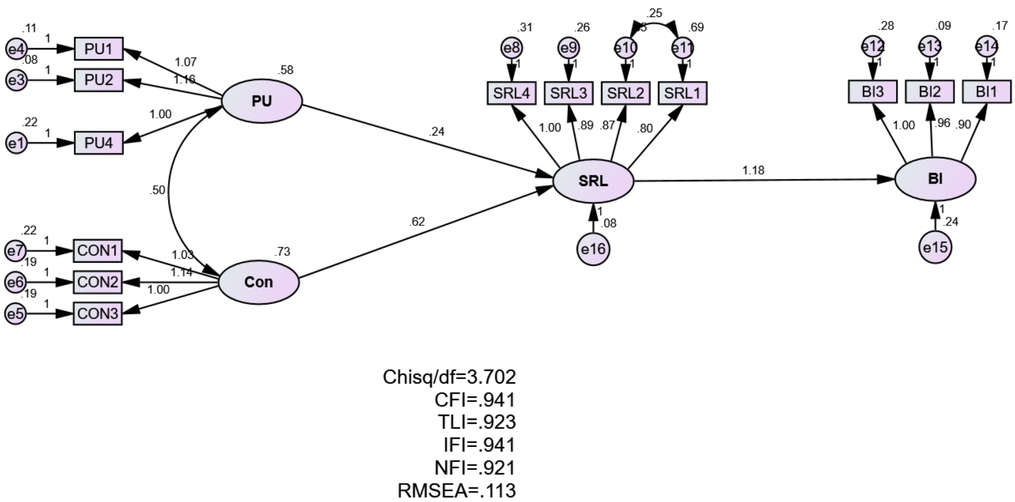

Figure 5. Unstandardized Estimates

Regression Weights

The results provide strong empirical support for all proposed hypotheses. First, PU had a significant positive effect on SRL (β = 0.235, p < .001), indicating that when students perceive e-learning systems as useful, they are more likely to engage in self-regulatory behaviors such as planning, monitoring, and evaluating their learning (H1 supported). Second, confirmation emerged as a stronger predictor of SRL (β = 0.624, p < .001), suggesting that when students' expectations of the e-learning system are met or exceeded, their motivation to self-regulate their learning is substantially enhanced (H2 supported). Finally, SRL exerted a very strong positive effect on BI to utilize e-learning systems (β = 1.182, p < .001), confirming that students who actively regulate their learning are more likely to continue adopting and relying on e-learning platforms (H3 supported). Collectively, these findings underscore the pivotal role of SRL as a mechanism linking system-related factors (PU and confirmation) to students' intention toward e-learning. The results are summarized in Table 5.

Table 5. Hypothesis Testing

Hypothesis	**Path**			Estimate	S.E.	C.R.	P	Hypothesis Testing
H1	SRL	<---	PU	.235	.071	3.300	*** ($p < .001$)	Supported
H2	SRL	<---	Con	.624	.072	8.650	*** ($p < .001$)	Supported
H3	BI	<---	SRL	1.182	.094	12.632	*** ($p < .001$)	Supported

Discussion

The findings of this study provide more understanding about the mechanisms that drive student behavioral intention to utilize e-learning systems in the context of PU, confirmation and SRL. First, the study's findings reveal that PU has a positive and significant effect on SRL ($\beta = 0.235$, $p < 0.001$). This shows that when a student believes an e-learning system will help them with their academic task, the student will be more likely to use self-regulation strategies, for instance, monitoring, planning and evaluation of their learning. This finding confirms research that has identified PU as an important contributing factor in learner engagement and self-regulatory behavior (Liaw & Huang, 2013; Gökçearslan et al., 2016). Therefore, students who see the utility of an e-learning platform will be more inclined to take control and self-regulate their own learning. Second, confirmation was a significant predictor of SRL ($\beta = 0.624$, $p < 0.001$), which was even more significant than the effect of PU. This indicates that in measuring SRL, confirmation of students' own proposition of e-learning system was key to self-regulation. If learners have confirmation of what they expected the system to accomplish whether it was the quality of content, usability, or accessibility, it will help provide motivation for the regulation of their own learning (in various other forms and strategies relevant). This is consistent with a study of Bhattacherjee's (2001) and extends ECM to imply SRL is a result of confirmation by students in e-learning context.

Finally, we found that SRL had a very strong and positive effect on BI ($\beta = 1.182$, $p < 0.001$) which indicates the importance of SRL as a predictor of students' intention to utilize e-learning systems. Students who self-regulate their study or learning will perceive wider value of e-learning in the long-term sense, which will then strengthen their continued intention to use e-learning. This result aligns with previous studies that have associated SRL to persistence, motivation, and technology adoption (Anthonysamy et al., 2020; Vanslambrouck et al., 2019), whilst providing new evidence for the direct pathway from SRL to BI in digital learning environments.

Theoretical Implications

These findings extend ECM framework by including SRL as a vital construct relevant to system-related factors (PU and confirmation) and behavioral intention. Whereas satisfaction has been traditionally established as the significant mediator in ECM studies (Bhattacherjee, 2001), this study has shown the potential for SRL to be an equally important mechanism, particularly in self-directed e-learning contexts. The findings indicate that not only does SRL mediate both relationships, it also contributes to the explanatory effectiveness of ECM, allowing for a better explanation of learners' intentions for continuance.

Practical Implications

From a practical perspective, the strong influence of confirmation on SRL suggests that e-learning platforms must ensure that students' expectations are consistently met through high-quality content, reliable technical performance, and responsive support services. Furthermore, system designers and educators should integrate features that explicitly foster SRL, such as goal-setting tools, progress dashboards, and self-monitoring prompts. By enhancing students' capacity to regulate their own learning, institutions can promote long-term adoption of e-learning systems.

Limitations

Although this study offers valuable findings, several limitations should be acknowledged. First, the utilization of a cross-sectional design might limit the ability to draw causal inferences about the relationships among constructs. Future research could employ a longitudinal design to capture changes in SRL and continuance intention over time. Second, the reliance on self-reported data may introduce common method bias or social desirability effects. Incorporating multiple data sources, such as system usage logs, could strengthen the validity of future investigations. Third, the sample was drawn from students in a single national context (Saudi Arabia), which may restrict the generalizability of the findings. Comparative studies across cultural or institutional settings would provide deeper insights into the role of SRL in e-learning adoption. Furthermore, in future research, we could build on the model and include other learner-related factors that may be associated with SRL and affect behavioral intention, such as technology anxiety, digital literacy, or perceived playfulness. In addition, we could use qualitative approaches, such as interview or focus group formats, to provide better insight into how students expressed their use of SRL strategies in an e-learning environment.

Conclusion

The purpose of this study was to extend the ECM by adding SRL as a core construct to explain students' BI toward using e-learning systems. In particular, the study investigated the direct effects of PU and confirmation on SRL and the direct effect of SRL on behavioral intention (BI). Using SEM with 214 university students, the study found that both PU and confirmation positively and significantly influence SRL, and that SRL is a strong predictor of BI. This study theoretically contributes to the ECM because it considered SRL a vehicle linking system-related perceptions (PU and confirmation) with intention. While much of the ECM-informed research has focused on satisfaction as the dominant mediator (Bhattacherjee, 2001), this study demonstrated that SRL is equally as important because it is necessary for self-directed digital learning. Thus, the study makes a valuable contribution to the literature on technology adoption in education by offering an improved explanation of students' sustained use of e-learning systems. This study has practical implications because it reinforces designing e-learning systems not only as useful and reliable, but also in a manner that embraces the students' self-regulation. e-learning systems have front-facing features such as dashboards allowing users to view their progress, goal reminders, and interactive feedback, all of which support students in better regulating their e-learning studies. In addition, institutions need to meet expectations for learners, as confirmation emerged as a remarkably strong antecedent of

SRL. As both of these constructs are met (useful and reliable systems, and meeting students' expectations), we can increase motivation and learner persistence concerning long-term adaptation of an e-learning system. Overall, the study highlighted that SRL is not just a learning outcome or process, it is also a strong predictor of students' intention to continue using an e-learning system. Thus, by confirming that PU and confirmation positively impact SRL, and that SRL strongly influenced BI, we demonstrated that sustaining digital learning necessitates a recognition of two-way influence of system quality and learner capability. The higher education sector should commit to fostering SRL for all students who, by their own volition, will hopefully re-engage with, and reap the long-term benefits of e-learning systems in their academics. This study contributed to theories, as SRL could be incorporated within ECM as a core construct, explaining how e-learning systems can be intentionally designed to encourage SRL, and raise students' continuance intention.

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