



Modelling STEM learners' academic performance in advanced level secondary schools with smart classrooms in Rwanda

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Abstract

Smart classroom setting is an effective technology-enhanced pedagogy when an instructor capitalises on the key drivers underlying its success. The objectives of the study are twofold. First, to investigate the factors that impact learners' academic performance in the smart classroom setting. Second, to determine whether learners' performance varies based on their gender and prior experience in the smart classroom. Three schools were selected and sampled from a pool of public advanced level (A' Level) STEM secondary schools with smart classrooms in Rwanda because they were among the first to set up smart classrooms. Data were randomly obtained from 389 learners, majoring in six different combinations. Exploratory factor analysis (EFA) was used to assess the validity and reliability of the measurement scale. A valid and thought-provoking learners' academic performance model, to enhance their learning outcomes, is presented. The model was validated using Structural equation modelling (SEM). The results indicated that technology self-efficacy, perceived ease of use, and learning satisfaction were all predictors of learners' performance. Learners' perceived ease of use and satisfaction were direct predictors of their performance. Besides, learners' perceived ease of use and usefulness were directly affected by technology self-efficacy. On the other hand, technology self-efficacy indirectly impacts learners' performance. The invariance analysis across gender groups revealed that male learners perceive smart classroom technology to be easier to use than females. Meanwhile, no evidence of metric invariance estimation of experience was found. We argue that effective pedagogical approaches can mitigate gender disparities in perceived usability of smart classroom technologies.

Keywords Smart classroom · Learning technologies · Academic performance · A' Level STEM secondary schools · Rwanda

Ngendahayo Emmanuel and Jean Baptiste Habarurema have equally contributed to this article, and therefore should be considered as first authors.

Extended author information available on the last page of the article

1 Introduction

The growing demand to incorporate digital technologies into education has forced schools all over the world to re-evaluate their pedagogical practices. The main goal is to train students to use those technologies to gain necessary knowledge and skills they need in the future. The Smart Classroom (SCL) is one of the ongoing projects in this direction. SCL is viewed as a breakthrough and a catalyst for technological changes, regardless of a country's economic standing, be it affluent or less privileged.

SCL is a promising platform to keep students digitally engaged and enable them to create their own knowledge through a seamless interactive learning experience (UNESCO, 2018). It is also the technology-enhanced learning environment which aims at bridging learning technologies gap between African and global education, and hence promote the mechanisms through which developing nations and their partners share experiences about learning technologies (African Union, 2018; UNESCO, 2018). Reports claim that SCLs are more effective in making difficult and complex scientific concepts easier and simpler for learners to understand (African Union, 2018, 2020; UNESCO, 2018).

Specifically, nearly half of Rwandan secondary schools are equipped with SCLs learning technologies (Office of Auditor General, 2021). Their goals are projected to improve quality of education through the digitally enhanced learner-centred environment, natural learner-teacher interaction flexibility and opportunities, and the strategies to assist teachers in overcoming their attitudinal barriers to pedagogical technologies. Similarly, other studies have claimed that the effectiveness of SCLs is mainly depicted in learning engagement systems and seamless interactions (Shadieff and Dang, 2022; Wooten, 2020; Yu et al., 2022), access to digital resources, immersive and personalised learning (Hwang, 2014; Spector, 2014; Zhu et al., 2016), collaborative higher order thinking skills (Venkatraman et al., 2022), and diversified learner-centred pedagogical approaches (Tabuenca et al., 2021).

In this paper, we define SCL as a physical teaching-learning environment with installed technology-enhanced infrastructures such as computers, wireless internet, networking and audio-visual equipment, projectors, smartboards, as well as digital contents, that foster pedagogical comfortability, flexibility, and interaction opportunities using multi-dimensional approaches (i.e., integrating diversified pedagogical, environmental and technological aspects). SCLs, like other technology-enhanced learning environments, effectively increase learner's satisfaction (LSAT) and academic performance (LAP). Given that no single study had yet validated the learners' LAP instrument or studied the causes of learners' LAP in SCLs in the African context, the current study asked the following questions to fill this knowledge gap.

- What are the factors that predict learners' academic performance (LAP) in the smart classroom setting?
- Do gender and previous experience in the smart classroom setting matter in predicting learners' academic performance (LAP)?

2 Literature review

Studies comparing traditional and SCLs are increasingly becoming more and more popular in academia. Yu et al. (2022), For example, compared the two in terms of learning engagement and interaction behaviours using a quasi-experimental design method. Their study found that students were more actively engaged in SCL than in traditional one, but no difference was detected in terms of interpersonal or human–technology interaction. They concluded that the interplay between pedagogy, space, and technology would best promote students’ seamless interaction. Similar studies (Lin, 2019; Ling & Chen, 2023; Saeed et al., 2021; Yi et al., 2021; Zhu et al., 2018) show that learners in SCL are more likely to outperform their traditional peers in learning outcomes, problem-solving ability, learning motivation, and learning interaction as well.

The purpose of the current research is to investigate the factors that impact learners’ satisfaction and their performance in the smart classroom setting, as well as to determine whether learners’ performance differs based on their gender and prior experience in the smart classroom. It is theoretically framed using Davis’ (1989) technology acceptance model (TAM) along with additional constructs of interest such as SCL technology self-efficacy (Lu et al., 2022), learners’ satisfaction (LSAT) (Islam, 2014; Joo et al., 2018) and learners’ academic performance (LAP) (Alyoussef, 2021), adapted from literature. The TAM model was chosen as the primary theoretical framework because it operates under the premise that how much users accept and adopt technological components dictates the extent to which they will successfully use it. As a result, this study assumes that when learners adopt SCL technology components, they are more likely to complete a certain task and so improve their learning outcomes. More details about the model specification and the hypothesised structure can be seen in 2.2 and in Fig. 1 respectively.

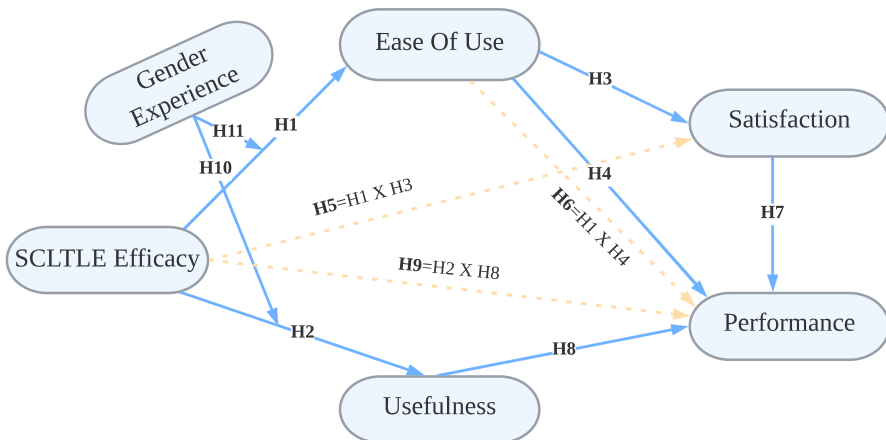


Fig. 1 The hypothesised structural academic performance (LAP) model

2.1 Smart classroom, learners' satisfaction and performance

SCL is more than just pouring ICT resources into traditional classrooms, it is about using those technologies to make a difference. It is about experimenting with novel pedagogy approaches that are compatible with those technologies, and it is about integrating learners into the main body of instructional activities. In this sense, learners develop their own learning strategies independently and as a result, their creative potential is fostered (Zhao, 2022). If properly well managed and exploited, SCL is more effective in enhancing LSAT and, ultimately, their LAP (Venkatraman et al., 2022; Yi et al., 2021; Yu et al., 2022).

Al-Azawei and Lundqvist (2015) researched that learners' expectations (performance) are directly and undeniably related to how satisfied they are with their own learning. Learning satisfaction is described as a transient psychological appraisal of a good education service provided (Elliott and Healy, 2001) or simply the learner's awareness of the value of what was received (Wu et al., 2010). Overall, literature (i.e., Chandra et al., 2019) links the quality of service and learners' achievement (Annamdevula and Bellamkonda, 2016), largely affirming that LSAT plays a crucial role in determining how well they perform in a technologically enhanced learning environments (Al-Azawei & Lundqvist, 2015; Alyoussef, 2021; Jung, 2014; Rasheed et al., 2022; Togaibayeva et al., 2022).

2.2 Theoretical foundation and hypotheses

Davis' (1989) technology acceptance model (TAM) has been and is essential for explaining and evaluating the tendency of user's technology acceptance behaviour in a variety of contexts and technology types. It asserts that as long as learners perceive well the usability or perceived ease of use (PEOU) and utility or perceived usefulness (PU) of technological tools to which they enjoy access, then they are more likely to develop a positive attitude towards the technologically enhanced learning system as a whole. This improves their learning experience, fosters a high degree of LSAT and increases the likelihood that they may use the same system again in the future. Thus, of the six constructs of Davis' (1989) TAM, PEOU and PU are the biggest predictors of learners' LSAT (Alyoussef, 2021; Joo et al., 2018). PEOU describes the extent to which the learners feel they were able to adapt to a new technology, whereas PU describes how much learners feel their LAP on the task improved as a result of using technologies.

SCL technology Self-efficacy influences one's behaviour performance attainment. In ICT related fields, Self-efficacy is described as a degree to which an individual believes he or she possesses the required knowledge and skills to execute an assigned task with relatively meaningful and desired results (Bandura, 1977). MacCallum and Jeffrey (2013) investigated whether ICT skills are among the factors that predict tertiary students' adoption of mobile learning. Their study was designed using the TAM framework in a sample of 446 students. Their findings revealed that ICT skills, among others, substantially influenced students' intention to adopt

mobile learning. Students with sophisticated mobile technology skills are more likely to perceive mobile learning as useful as easy to use.

Liu and Grandon (2003) investigated how performance and domain specific (DS) self-efficacy moderated by prior attended training influenced individual PEOU of DS self-efficacy. Their study confirmed that the effect of DS self-efficacy on PEOU was significantly positive and becomes weaker when people are given prior training in structured analysis, while the association between performance and PEOU becomes positively stronger when people are given the same training and possess necessary DS self-efficacy. They concluded that prior training experience moderated the effect of DS self-efficacy on both PEOU and performance in a structured manner. Venkatesh and Davis (1996), on the other hand, claimed that computer self-efficacy (CSE) affects PEOU regardless of whether or not an individual has experience. Islam et al. (2018) found that CSE had a positive direct effect on learners' PEOU and PU of wireless internet use in higher education (HE). Recently, Jiang et al. (2022) established that CSE had a positive direct effect on students' PEOU and PU of e-learning platforms. Drawing up on the above findings, the study puts that,

H1: Learners' smart classroom (SCL) technology self-efficacy has a significant positive direct effect on their perceived ease of use (PEOU).

H2: Learners' smart classroom technology self-efficacy has a significant positive direct effect on their perceived usefulness (PU).

Previous research (i.e., Islam et al., 2018) found that PU and PEOU had a significant direct effect on LSAT in using wireless internet in HE. Joo et al. (2018) claimed that PEOU influenced students' academic credits and certificates attainment in a 16-week MOOC training programme. Bossman and Agyei (2022) omitted PU in favour of PEOU as a significant predictor of LSAT and LAP in an e-learning setting, confirming that PEOU had a significant positive direct effect on both LSAT and LAP. Islam et al. (2018) confirmed that PEOU played a significant mediator role in the association between students' CSE and their LSAT when using a computer and wireless internet in HE. In a similar study, Islam et al. (2018) also confirmed the indirect effect of CSE on LSAT through PEOU. Thus, the study anticipates that,

H3: Perceived ease of use (PEOU) has a significant positive direct effect on learners' satisfaction (LSAT).

H4: Perceived ease of use (PEOU) has a significant positive direct effect on learners' academic performance (LAP).

H5: Perceived ease of use (PEOU) mediates a significant positive indirect effect of smart classroom (SCL) technology self-efficacy on learners' satisfaction (LSAT).

H6: Perceived ease of use (PEOU) mediates a significant positive indirect effect of smart classroom (SCL) technology self-efficacy on learners' academic performance (LAP).

Literature shows that LSAT predicts LAP in the technologically enhanced learning environment. Jung (2014), for example, incorporated ubiquitous learning

characteristics into the TAM model to evaluate students' LSAT in ubiquitous language learning and found that CSE had positive direct and indirect effects on LSAT and LAP respectively. In a similar study, Jung (2014) also discovered that LSAT moderated the effect of CSE on LAP. Rasheed et al. (2022) found that LSAT mediated the association between service quality dimensions and LAP among e-learning students. Bossman and Agyei (2022) affirmed that LSAT is the major predictor of LAP among e-learning students, and claimed that other factors such as instructor factors would not enhance their LAP in the absence of LSAT. In similar studies (Alyoussef, 2021; Dinh et al., 2022; Togaibayeva et al., 2022), LSAT had a positive direct influence on LAP. Based on the prior studies, the study puts that,

H7: Learners' satisfaction (LSAT) has a significant positive direct effect on their academic performance (LAP).

Chavoshi and Hamidi (2019) identified four group factors, one of which was PU of mobile phones, that impact students' LAP in mobile learning settings. The results of their study showed that students' PU was the most significant predictor of LAP. Recently Togaibayeva et al. (2022) investigated the impact of mobile learning on LSAT, PU and their LAP. Their study confirmed the positive direct effect of PU of mobile learning on students' LAP when learning foreign languages. In a similar study, Reddy et al. (2022) established that students' positive attitudes and perceptions to use mobile phones in a mobile learning setting make learning more exciting and thus, contributes to university studies success. Alyoussef (2021) claimed that PEOU had a positive effect on perceived enjoyment and PU, which in turn affected task–technology fit and e-learning platform usage in HE, resulting in a positive effect on students' LSAT, their LAP and sustainability as well. Thus, against this backdrop, the study puts that,

H8: Learners' perceived usefulness (PU) has a significant positive direct effect on their academic performance (LAP).

H9: Learners' perceived usefulness (PU) mediates a significant positive indirect effect of smart classroom technology self-efficacy on their academic performance (LAP).

Islam et al. (2018) confirmed that gender exerted an effect as a moderator towards students' LSAT in using wireless internet in HE. In a recent study, Izkair and Lakulu (2021) investigated the experience moderator variable effect on the factors (i.e., effort expectancy, social influence, facilitating conditions, performance expectancy, and satisfaction) that influence students' and staffs' intention to use mobile phones. Their study indicated that experience moderated the effect of effort expectancy, social influence, and performance expectancy on their intention to use mobile phones. Thus, the study anticipates that,

H10: Gender moderates the effect of smart classroom (SCL) technology self-efficacy on (a) perceived ease of use (PEOU) and (b) perceived usefulness (PU).

H11: Gender and experience have moderating effects on learners' academic performance (LAP) in a smart classroom setting.

H12: Learners' smart classroom experience moderates the effect of smart classroom (SCL) technology self-efficacy on (a) perceived ease of use (PEOU) and (b) perceived usefulness (PU).

This study is structured as follows: It begins with an introduction, context and purpose of the study, and then moves on to a review of relevant existing knowledge about the topic and what it adds. The theoretical framework is discussed in the second section, while the third section discusses the methods used before presenting the results of hypothesised learners' academic performance (LAP) model. Finally, conclusion is drawn, along with implications for practice and limitations of the study.

3 Methods

This study uses a cross-sectional design. Prior to the study, ethical approval was obtained from respective districts where the case studies of interest are located. Principles of the respective schools were also contacted and granted us permission to collect data in early.

February 2023. Prior to data collection, the researcher conducted an observation study in the respective smart classrooms and interviewed a relative number of teachers and learners to inform the study questionnaire adaptation and proper modification, and to gain a thorough understanding of how smart classroom technologies are being used to enhance learning outcomes.

3.1 Participants

The population of the study consisted of A' level learners majoring in science, technology, engineering and mathematics (STEM) disciplines in Rwanda's public secondary schools. These schools were specifically chosen because they were among the first schools to establish smart classrooms. Because of time and financial constraints, only three schools were sampled. The sample comprises two subsamples. The first subsample included 122 learners from three schools: X, Y and Z. They are geographically located in different districts and provinces in Rwanda (X is located in Nyarugenge district in Kigali city, while Y and Z are in Ruhango district in Southern Province). After data cleaning, only 116 learners (72 female or 62.1% and 44 male or 37.9%) were included in the final Exploratory Factor Analysis (EFA). This sample was used to measure the dimensionality of items on each construct using the EFA method.

The second subsample consisted of 412 participants, obtained from the same schools of X, Y and Z. Of 412, only 389 (175 female or 45% and 214 male or 55%) were included in the final analysis. There was no outlier identified. Only 9 incomplete and 14 unengaged responses whose standard deviation is <0.25 were dropped. This sample was used to evaluate the measurement model, fit the model and to test

hypotheses using Confirmatory Factor Analysis (CFA). The demographic profile of respondents is shown in Table 1.

3.2 Measures and procedures

The study utilised a modified version of a scale that had been established in literature. It was somewhat modified and adjusted to match the current study objectives. As suggested by Ehido et al. (2020), the scale was also validated in Rwandan context since it was adapted and modified from various literature and cultures.

The scale consisted of two parts. Part 1 included seven questions (gender, age, learners' experience in SCL setting, nationality, grade, combination and school name) concerning demographic information of respondents. While the scale questions were in part 2. The later has 48 items with 5 components: SCL technology self-efficacy (SCLSE, 10 items) adapted from Arbaugh (2000), PU (10 items) and PEOU (9 items) adapted from Arbaugh (2000) and Islam (2014), LSAT (12 items) from Arbaugh (2000), while learners' LAP (7 items) items were adapted from Alyoussef (2021). All items were measured on a 5-point Likert scale ranging from 1 "strongly agree" to 5 "strongly disagree". Afterwards, learners were instructed about

Table 1 Demographic profile of the respondents

Characteristics	Categories	Frequency	Percentage (%)
Gender	Male	214	55
	female	175	45
Age experience	Between 16–20	386	99.2
	Between 20–25	3	0.8
	Less than 5 months	13	3.3
	6–11 months	11	2.8
	1 year and 11 months	9	2.3
	2 Years or above	356	91.5
Grade	Senior 4	33	8.5
	Senior 5	127	32.6
	Senior 6	229	58.9
Combination	MCB	145	37.3
	MPG	33	8.5
	MPC	28	7.2
	MCE	27	6.9
	PCB	43	11.1
	PCM	113	29.0
School	X	141	36.2
	Y	182	46.8
	Z	66	17

MCB Mathematics-Chemistry & Biology, *MPG* Mathematics-Physics & Geography, *PCM* Physics-Chemistry & Mathematics, *PCB* Physics-Chemistry & Biology, *MPC* Mathematics-Physics & Computer Science, *MCE* Mathematics-Chemistry & Economy

the questionnaire and its objectives and were requested to voluntarily complete its printed version. After obtaining their consents, questionnaires were randomly distributed to them. It took roughly 20 min to return their responses to their respective teachers.

3.3 Data analysis

To analyse the study data, several methods were performed. Firstly, Exploratory Factor Analysis (EFA) was used to analyse the dimensionality and the factor loadings for each construct considered in the study, using SPSS 26 Software. Afterwards, AMOS 26 Software was used to conduct the Confirmatory Factor Analysis (CFA) to establish the measurement model, fit the model and to test hypotheses.

4 Results

The EFA and CFA results are presented in the following sections.

4.1 Exploratory Factor Analysis (EFA)

Previous studies (i.e., Hair et al., 2010; Malhotra, 2020; Zainudin, 2015) explained why EFA should be performed. First, EFA can be employed to determine and decide the suitability and usefulness of items for each construct under the study based on their factor loadings and dimensionality. Second, EFA is used to assess the validity, reliability of measurements of the constructs. Third, EFA is used to examine the relationship among items of each construct in the study. Fourth, EFA can be used to evaluate the quality of research instruments in terms of culture, language, study subjects, and time-lapse, allowing researchers to eliminate weak items prior to further analysis. Finally, EFA can be used to re-validate the adapted scale whose items were slightly modified and adjusted to fit in the context of the study and its objectives.

Thus, EFA was used to achieve the above-mentioned reasons. SPSS 26 was employed to run EFA. Firstly, the Principal Component Analysis using Varimax rotation method with eigenvalues > 1 was used. The rotation findings in Table 2 show that the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was satisfactory at 0.849, with a P-value considerably > 0.05 . EFA was run because the sample adequacy test was > 0.6 with significant value > 0.05 , which is sufficient to conduct factor analysis (FA) (Hair et al., 2010; Malhotra, 2020; Zainudin, 2015). These findings allowed us to perform FA by item reduction in EFA.

Table 2 KMO and Bartlett's Sphericity Tests

KMO measure of sampling adequacy.		0.849
Bartlett's Test of Sphericity	Approx. Chi-Square	1416.785
	df	276
	Sig.	0.000

Table 3 Total variance explained

Component	Initial eigenvalues			Rotation sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.677	31.986	31.986	7.677	31.986	31.986
2	2.557	10.654	42.641	2.557	10.654	42.641
3	2.153	8.969	51.610	2.153	8.969	51.610
4	1.728	7.198	58.808	1.728	7.198	58.808
5	1.464	6.101	64.908	1.464	6.101	64.908

Extraction method: Principal Component Analysis

Table 4 The items and components of academic performance

Component	No. of items	Items	Cronbach's Alpha for each sub-factor
1	3	SCLSE6, SCLSE7, SCLSE9	0.665
2	4	PU2, PU3, PU5, PU6	0.770
3	4	PEOU1, PEOU2, PEOU3, PEOU8	0.792
4	6	LSAT3, LSAT4, LSAT6, LSAT7, LSAT8, LSAT12	0.895
5	7	LAP1, LAP2, LAP3, LAP4, LAP5, LAP6, LAP7	0.896
All items	24	24	0.907

The EFA results presented in Table 3, revealed that five extracted components explain approximately 65% of the scale used in Rwandan context, with the remaining percentage being attributed to other factors. In other words, the total variance of 60% or even <60% is significantly acceptable in social sciences research (Hair et al., 2010).

In the second step, the EFA analysis was run by suppressing a small coefficient set to 0.50, as suggested in Hair et al. (2010) and Zainudin (2015). The results showed that few items had cross-loadings issues, which were then removed. Table 4 shows the number of items retained on each component, whereas Table 5 presents the pre-final version of the retained scale components and their respective items for CFA.

4.2 Estimating the academic performance (LAP) model

The final analysis, presented in Table 4, consisted of five components with 24 items and was estimated using structural equation modelling (SEM). Using SPSS AMOS 26, the CFA was performed on 24 items of learners LAP resulted from EFA. According to Hair et al. (2010) and Zainudin (2015), CFA is to evaluate unidimensionality, validity and reliability and to assess the measurement model, model fitness statistics and structural model. When the factor loading for each factor is >0.50, then the unidimensionality is passed. The CFA results presented in Fig. 2 indicated that the

Table 5 The components and their respective items

Rotated Component Matrix ^a					
	Component				
	Efficacy (SCLSE)	Useful (PU)	Ease of Use (PEOU)	Satisfaction (LSAT)	Performance (LAP)
SCLSE6	0.821				
SCLSE7	0.692				
SCLSE9	0.754				
PU2		0.724			
PU3		0.837			
PU5		0.693			
PU6		0.734			
PEOU1			0.731		
PEOU2			0.686		
PEOU3			0.785		
PEOU8			0.706		
LSAT3				0.718	
LSAT4				0.792	
LSAT6				0.853	
LSAT7				0.768	
LSAT8				0.685	
LSAT12				0.757	
LAP1					0.772
LAP2					0.765
LAP3					0.813
LAP4					0.733
LAP5					0.653
LAP6					0.716
LAP7					0.748

Extraction method: Principal Component Analysis

Rotation method: Varimax with Kaiser Normalisation

a. Rotation converged in 6 iterations

fitness indexes of the measurement model on the second order were achieved. Thus, we conclude that the validity and reliability of the LAP scale were met.

The model results also indicated neither negative loadings nor negative error variance. The overall goodness-of-fit statistics demonstrated an adequate fit with $\chi^2(df=246)=509.952$, $p < 0.001$ and the root mean square error of approximation (RMSEA) confirmed the model's adequacy at the acceptable value score of 0.053, which is substantially < 0.08 (Hair et al., 2010; Zainudin, 2015). However, the results presented in Fig. 2 suggested that there was still potential for model improvement because few items produced large modification indices (MI) and residual

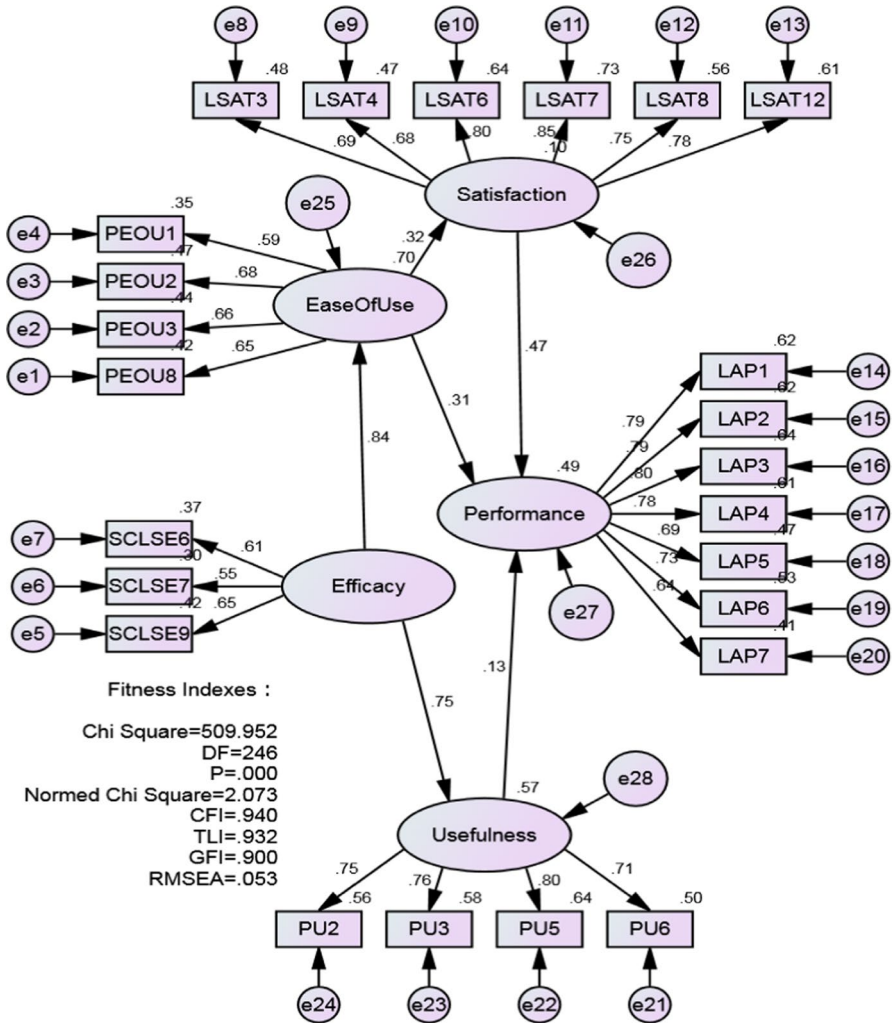


Fig. 2 The academic performance (LAP) Model

errors, indicating that there might be multicollinearity issues, which necessitated the model revision. Figure 3 presents the revised LAP model.

It can be observed that the model’s measurement items loaded significantly on their respective constructs with values > 0.50, indicating that the construct validity was attained (Zainudin, 2015). The average variance extracted (AVE) and composite reliability (CR) were also calculated to examine the indicators’ convergent and discriminant validity and reliability. Table 6 shows that AVE and CR were achieved with values > 0.50 and 0.70 respectively, as advised by Zainudin (2015). Thus, based on the significant value of CR > 0.70 alone, we can conclude that the validity and reliability of the constructs is satisfactory (Malhotra, 2020, P702).

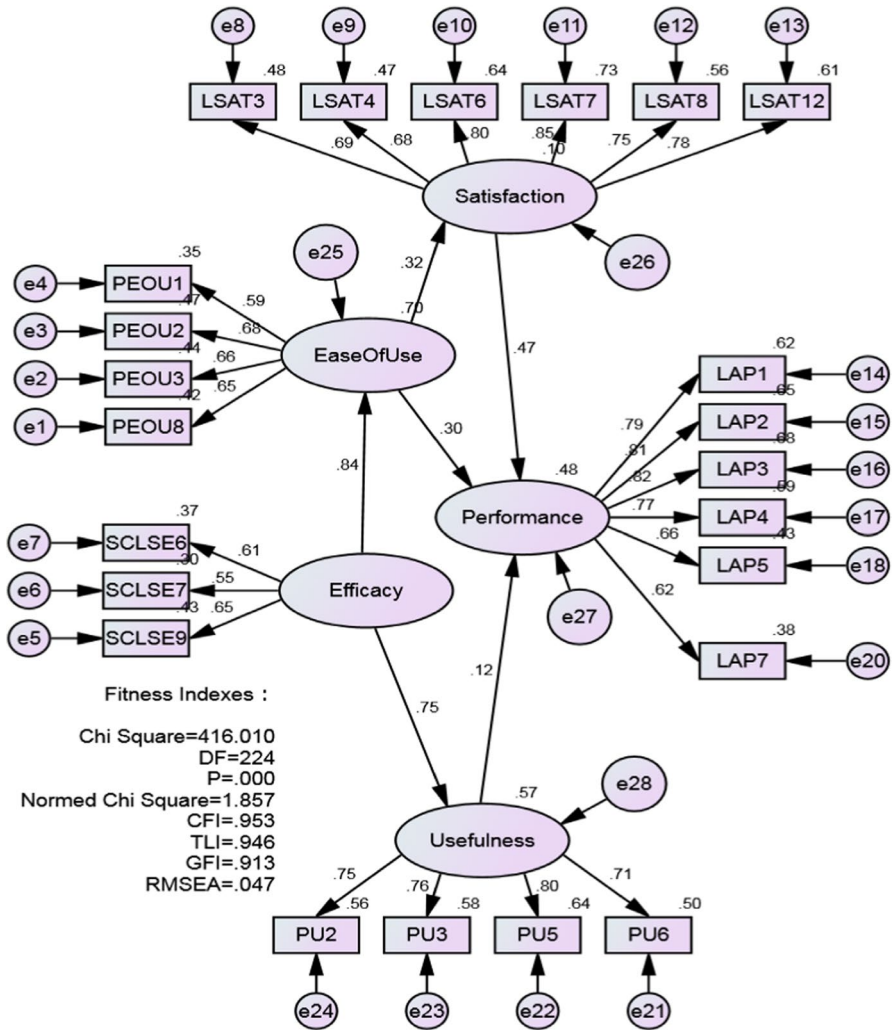


Fig. 3 The revised academic performance (LAP) Model

4.2.1 The revised academic performance (LAP) model

The LAP model was revised. Its global and local fitness indexes were reexamined to assess the overall fitness indexes. In the revising process, one item (LAP6) was removed because it was producing multiple large residuals and large modification indices (MI). After the removal of LAP6, a total of 23 items remained. The results presented in Fig. 3 demonstrates the fitness indexes improvement which otherwise would have not been obtained from free parameter technique (Zainudin, 2015). It also depicts the improved results, which indicate a significant model improvement free from negative loadings and path coefficients. The factor loadings of the revised

Table 6 The results of Average Variance Extracted (AVE) and Composite Reliability (CR)

Component	Item	Factor loading	CR > 0.6	AVE > 0.5	Mean	SD
Efficacy (SCLSE)	SCLSE6	0.821	0.801	0.574	3.93	1.12
	SCLSE7	0.692				
	SCLSE9	0.754				
Usefulness (PU)	PU2	0.724	0.836	0.561	4.17	0.99
	PU3	0.837				
	PU5	0.693				
	PU6	0.734				
Ease Of Use (PEOU)	PEOU1	0.731	0.818	0.530	4.10	1.04
	PEOU2	0.686				
	PEOU3	0.785				
	PEOU8	0.706				
Satisfaction (LSAT)	LSAT3	0.718	0.893	0.584	3.28	1.35
	LSAT4	0.792				
	LSAT6	0.853				
	LSAT7	0.768				
	LSAT8	0.685				
	LSAT12	0.757				
Performance (LAP)	LAP1	0.772	0.896	0.554	4.06	1.08
	LAP2	0.765				
	LAP3	0.813				
	LAP4	0.733				
	LAP5	0.653				
	LAP6	0.716				
	LAP7	0.748				

model range from 0.55 to 0.85, indicating statistically significant loadings (Hair et al., 2010; Zainudin, 2015). The overall model fit statistics show the significant fit: $\chi^2(df=224)=416.010$, $p<0.001$, RMSEA=0.047, GFI=0.913; CFI=0.953; TLI=0.946.

Furthermore, the estimated positive direct effects of Learners' SCL technology self-efficacy (SCLSE) on both the PEOU ($b=0.84$, $p<0.001$) and PU ($b=0.75$, $p<0.001$) of the SCL were supported, confirming H1 and H2. The positive direct effect (H3) of PEOU ($b=0.32$, $p<0.001$) of SCL on LSAT was supported; the positive direct effect (H4) of PEOU ($b=0.30$, $p<0.001$) of SCL on LAP was supported; the mediating role (H5) of PEOU ($b=0.266$, $p<0.001$) of SCL on the relationship between SCLSE and LSAT was supported. Likewise, the mediating role (H6) of PEOU ($b=0.254$, $p=0.002$) of SCL on the association between SCLSE and LAP was also supported. Similarly, the H7 which predicted the effect of learners' LSAT ($b=0.47$, $p<0.001$) of SCL on their LAP was supported. The Learners' PU ($b=0.30$, $p=0.081$) of SCL, on the other hand, predicting the positive direct effect (H8) of PU on LAP, was confirmed to be statistically insignificant. Likewise,

Table 7 Hypothesis testing results

Hyps	Direct Paths		Path Coeff.		P-Value	Conclusion	
H1	SCLSE → PEOU		0.84		0.001***	Supported	
H2	SCLSE → PU		0.75		0.001***	Supported	
H3	PEOU → LSAT		0.32		0.001***	Supported	
H4	PEOU → LAP		0.30		0.001***	Supported	
H7	LSAT → LAP		0.47		0.001***	Supported	
H8	PU → LAP		0.30		0.081†	Rejected	
Hyps	Indirect paths	Unstandardised Estimate	Lower	Upper	P-Value	Standardised Estimate	Conclusion
H5	H1 X H3	0.402	0.271	0.568	0.001	0.266***	Supported
H6	H1 X H4	0.380	0.205	0.619	0.002	0.254***	Supported
H9	H2 X H8	0.133	0.015	0.280	0.067	0.089†	Rejected

Significance of estimates: *** $p < 0.001$; ** $p < 0.010$; * $p < 0.050$; † $p < 0.100$

the results rejected the estimated mediating effect (H9) of learners' PU ($b = 0.089$, $p = 0.067$) of SCL on the association between learners' SCLSE efficacy and their LAP. All these hypotheses' results are highlighted in Table 7.

4.3 Interaction analysis

The H10, H11 and H12, which anticipated the moderating effects of gender and SCL experience (low & high) groups on the positive relationship between SCLSE and PEOU of SCL technology, as well as the association between SCLSE and PU of SCL technology, were tested.

First, the moderating effect of gender on the relationship between SCLSE and PEOU was tested using Chi Square (χ^2) and the degree of freedom (df) difference between the unconstrained and structured models. The findings revealed that gender groups vary ($\chi^2(df=2) = 6.973$, $p = 0.031$) in their PEOU of SCL technology. Afterwards, the standardised estimates of the model indicated that PEOU is stronger in males at 0.85 than females at 0.82. That is, their PEOU level of SCL technology self-efficacy varies across gender groups. In other words, male learners perceive SCL technology to be easier to use than females. These findings support the H10a. The invariance ($\chi^2(df=2) = 6.970$, $p = 0.031$) results can be seen in Table 8. Similarly, the moderating effect of gender on SCLSE and PU was also tested. The results presented in Table 8 rejected the H10b confirming that no variance ($\chi^2(df=2) = 4.746$, $p = 0.093$), between groups, was identified. That is, the study indicated no difference, between gender groups concerning learners' PU of SCL technology, was identified. In this case, the study observed no evidence that either gender or learners' SCL technology experience moderated the association between the SCLSE and PEOU, as well as the SCLSE and PU at the model level, rejecting H11 estimation.

Second, the H12 predicting the moderating effect of SCL experience on the association between SCLSE and PEOU, as well as the association between SCLSE and PU, were also evaluated using χ^2 score and the df invariance between the unconstrained and structured models. The SCL experience variable was categorical and

Table 8 Interaction effects

Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho2
[Gender moderation effect on SCLSE and PEOU and PU]							
[H10] Structural Weights:							
(a) SCLSE → PEOU	2	6.970	0.031*	0.001	0.001	0.000	0.000
(b) SCLSE → PU	2	4.746	0.093	0.001	0.001	0.000	0.000
[H11] Structural Weights:							
Gender → LAP	48	53.273	0.279	0.006	0.006	-0.004	-0.004
Experience → LAP	48	37.590	0.860	0.004	0.004	-0.007	-0.008
[Experience moderation effect on SCLSE and PEOU and PU]							
[H12] Structural Weights:							
(a) SCLSE → PEOU	2	0.284	0.868	0.000	0.000	0.000	-0.001
(b) SCLSE → PU	2	0.631	0.729	0.000	0.000	0.000	0.000

Significance of estimates: * $p < 0.050$

was categorised as low (less than one year of SCL experience), medium (1 year or more but less than two years of SCL experience), and high (2 years or more of SCL experience). Only two groups (low and high experience) were cross-compared. Table 8 shows that there is no group variance ($\chi^2(df=2)=0.284, p=0.868$) in terms of learners' PEOU of SCL technology, resulting in rejection of the H12a. H12b, predicting the moderating effect of SCL experience on the relationship between PU and SCLSE, was also tested. The results presented in Table 8 rejected our prediction, confirming that there was no group variance ($\chi^2(df=2)=0.63, p=0.729$) in terms of learners' PU of SCL technology.

5 Discussion

The objectives of the study were to investigate the factors that impact learners' performance in the smart classroom setting, and to determine whether learners' performance varies based on their gender and prior experience in the smart classroom. This research pioneers the adaptation, introduction, and validation of the academic performance (LAP) scale for use in Rwanda. It is also the first endeavour to investigate the factors of SCL technology in enhancing learners' LAP in the African context. Moreover, it generates considerable thought-provoking debate on how best to use technology enhanced SCL and the variables that educators might care most about in their daily teaching process. Thus, it is expected to give a more practical and appropriate experiences for the application of SCL technologies in enhancing learning outcomes not just in Rwanda, but also in other socioeconomically comparable nations.

The variables SCLSE, PEOU, LAST were validated and proved to be effective predicting factors of the LAP in the SCL. While the PU ($b=0.30, p<0.081$) variable slipped marginally with no effect on learners LAP. Learners' SCL technology self-efficacy (SCLSE) possesses the direct effect on how they perceive the utility (PU) and usability (PEOU) of SCL. However, SCLSE's indirect effect on both learners LSAT and LAP cannot be ignored. Meaning that SCLSE is a prerequisite and indispensable factor for learners' LAP. These findings are not strange in literature (Dinh et al., 2022; Islam, 2014; Islam et al., 2018; Jung, 2014; Lu et al., 2022; MacCallum and Jeffrey, 2013; Sökmen, 2021; Togaibayeva et al., 2022; Zhao, 2022).

Furthermore, the findings are also consistent with Jung (2014) claim that CSE self-efficacy positively influenced learners' LAP in a ubiquitous learning environment. Our findings, However, differ with those of Togaibayeva et al. (2022) who found that mobile learning technology self-efficacy had a positive direct influence on students' LSAT and LAP in learning a foreign language. Similarly, the results are inconsistent with those of Jung (2014) who discovered that students' characteristics (i.e., Ubiquitous learning self-efficacy) had a positive direct effect on their LSAT in a ubiquitous learning environment. These results imply that learners' SCLSE make them perceive smart classroom setting as usable and useful thereby leading to their LSAT and hence their LAP in the smart classroom setting.

The study establishes that the more the learners consider SCL technology to be user-friendly (PEOU), the more prominent their LSAT becomes, hence increasing their LAP. That is, SCL instructors should, in other words, consider how learners view the technological tools they use in SCL. These findings are consistent with literature (Bossman & Agvei, 2022; Joo et al., 2018).

Male learners consider SCL technology more user-friendly (PEOU) than females, whereas the study results did not discover any difference between gender groups in how useful (PU) the SCL technology is. This confirmed that gender moderates the relationship between SCLSE and PEOU, supporting the study estimation. The study, on the other hand, revealed that gender did not moderate the association between SCLSE and PU, rejecting the study prediction. These findings differ from those of Islam et al. (2018) who detected gender groups variance on the model level rather than the path level.

The estimation of SCL technology experience, predicting the association between SCLSE and PEOU, as well as the association between SCLSE and PU, was unexpectedly rejected. That is, the study discovered no variation in PEOU and PU of SCL technology across gender groups in SCL. This means that learners' SCL technology experience did not contribute to their PEOU and PU of SCL technology. This contrasts the recent study by Izkair and Lakulu (2021), which found that students' and academics' mobile learning experiences moderated the effects of their effort expectancy ($b=0.216, p=0.001$), their social influence ($b=0.219, p=0.005$), and their performance expectancy ($b=0.187, p=0.009$) on their perceived intention to use mobile learning.

The H7 predicting the effect of learners' LSAT ($b=0.47, p<0.001$) on their LAP was supported. That is, the learners' LAP is improved effectively when they are more satisfied with the SCL setting. This is supported by the literature (Alyoussef,

2021; Bossman & Agyei, 2022; Thamrin et al., 2023). In other words, these findings are adding up to the existing.

SCLs instructors' workloads by mandating that they should constantly educate their learners on the utmost importance of using various SCL technologies. They must also encourage their learners to use technologies in and out of classroom settings provided that those technologies have the potential to improve learning outcomes. In addition, instructors could establish clear pedagogical objectives to create technologically user-friendly SCL.

6 Conclusion

The objectives of the study were to investigate the factors that impact learners' academic performance (LAP) in the smart classroom setting, as well as to determine whether learners' performance (LAP) differs based on their gender and prior experience in the smart classroom setting. It was carried out in three phases. Firstly, the observation. By observing smart classroom technology facilities of the schools of interest (X, Y & Z) and conducting interviews with instructors and students about the use of SCLs. Secondly, conducting a pilot study with 116 valid learners' responses from the same schools, based on the observation findings. Thirdly, the printed paper format questionnaires were randomly administered to learners from respective schools, yielding a total of 389 valid responses.

Uni-dimensionality, validity and reliability of the measurements under each construct as well as sample size adequacy were checked using the EFA method, performed in SPSS. The later objectives were achieved, and the sample size was more than adequate, and more representative of the population because it was drawn from three separate schools located in different provinces across the country. The EFA results demonstrated that five extracted factors (Efficacy, Ease fuse, Usefulness, Satisfaction and Performance), consisted of 24 items explaining more than 60% of the performance scale used in Rwandan context. Afterwards, CFA analysis was performed using SPSS AMOS 26 software to evaluate the measurement model and the model fitness, both of which were significantly achieved.

The findings indicated that smart classroom (SCL) technology self-efficacy has positive direct effect on both perceived ease of use (PEOU) and perceived usefulness (PU), thereby validating H1 and H2 respectively. Technology self-efficacy mediated by perceived ease of use indirectly impacts learners' satisfaction. On the other hand, mediated by both PEOU and learners' satisfaction (LSAT), SCL technology self-efficacy has indirect positive influence on their performance. That is, SCL technology self-efficacy is very prerequisite to exert both direct and indirect effect as an exogenous variable to learners' satisfaction and performance in SCL setting. Learners' satisfaction (LSAT) becomes the second player in the model to necessitate and explain learners' performance (LAP) in the model. Whereas, PU did marginally fail to explain learners' performance (LAP).

Furthermore, the positive direct effect of PEOU of SCL on learners' satisfaction (LSAT) was supported, validating H3. On the other hand, the study validated the positive direct effect of PEOU on learners' performance (LAP), thereby validating

H4. The mediating effect of PEOU on the relationship between SCL technology self-efficacy and learners' satisfaction (LSAT) was also supported, validating H5. Likewise, the mediating effect of PEOU on the association between SCL technology self-efficacy and performance (LAP) was also supported, validating H6. Meanwhile, the H7 predicting the effect of learners' satisfaction (LSAT) of SCL technology on their Performance (LAP) was validated. Conversely, the direct effect of PU on their performance (LAP) was statistically insignificant, thereby rejecting H8. Likewise, the results discovered that the H9 predicting the mediating effect of PU on the association between their SC technology self-efficacy and performance (LAP) was statistically unsupported.

Interaction analysis, predicting the H10, H11 and H12, was also evaluated. At the model level, we found no evidence that either gender or SCL technology experience moderated the association between SCL technology self-efficacy and PEOU and the association between SCL technology self-efficacy and PU. Similarly, the results from SCL experience moderator indicated no moderating effect on either level. In contrast, the path results between SCL technology self-efficacy and PEOU of SCL technology revealed that gender groups vary in their PEOU. In this regard, PEOU was stronger in male than female. That is, male learners perceive SCL technology to be easier to use than female. Whereas, the results of the moderating effect of gender on association between SCL technology self-efficacy and PU indicated no difference between groups. That is, learners' PU is invariant across gender groups in the study.

Overall, the study subsequently lays out a foundational tool and gives a point of departure for researchers who wish to continue discussions in Rwandan context and beyond, notably in other socioeconomically comparable nations. More importantly, the study contends that academics must employ appropriate and effective pedagogical approaches to mitigate gender disparities in how their learners perceive the utility (PU) and usability (PEOU) of SCL technology, which affect their academic performance. In this regard, we assume that whatever causes disparities in how learners perceive PEOU and PU may also induce disparities in their academic performance (LAP).

7 Implications for practice

Overall, the objectives of the study were to investigate the factors that impact learners' academic performance in the smart classroom setting, and to determine whether learners' performance varies based on their gender and prior experience in the smart classroom. The findings revealed that while teaching, instructors must pay attention to learners' perception variations in terms of their PEOU of SCL technology. In other words, (1) *Instructors* should consider how their learners perceive the SCL environment. Gender is a significant factor to take into account in this regard; in particular, females should be given special consideration because they are more susceptible to SCL usability (PEOU) and perceive SCLT technology to be more challenging to use than males. Additionally, learners' level of SCL technology efficacy should be taken into account by defining clear and specific pedagogical objectives to arouse and cultivate their digital mindsets. More importantly, learners should be

encouraged, supported and guided to use technologies both inside and outside the classroom, if it is determined that doing so will improve their learning outcomes.

(2) *School administrators* should take necessary measures, such as continuously providing training to instructors to assist them overcome technology inertia and other attitudinal barriers to teaching and learning technologies. In addition, (3) *Policy practitioners, school administrators and instructors* should collaboratively establish measures to promote learning technology culture through curriculum and school culture. For example, promoting technology culture at school and/or classroom level could entail hanging simple banner graphics, technologically created photographs and other pertinent designs related to a particular course in classrooms and schools. Furthermore, the school administrations may also opt to implement incentivised mechanisms for incorporating digital technologies into education. This would not only foster technology culture, but also positive attitudes toward technology use among instructors and learners. At curriculum level, contents could be designed with the ability of learners and instructors to use technology tools in mind. In this regard, simple technological games could serve as a good beginning point. This would not just seek to achieve any pedagogical objective, but also to introduce new pedagogical approaches, generate new actionable ideas and new theories.

Finally, it is important to note that this study is not free from any limitation. The study is solely limited to Rwanda's advanced STEM secondary schools' learners, and also includes few variables. Future studies would consider expanding the theoretical foundation of the study, thereby increasing the number of variables, and open up the study to include other high school combinations (soft sciences) other than hard sciences (STEM). Furthermore, a mixed methods approach might reveal hitherto unexplored aspects in this work that would have otherwise been elaborated.

Data availability the dataset analysed during the current study are available from the corresponding author on a reasonable request.

Declarations

Competing interests There are no competing interests to declare.

Conflict of interest The authors declare no conflicts of interest.

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