The Moderating Effect of Education and Experience on the Use of Learning Management Systems

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ABSTRACT
Based on the technology acceptance model, this research investigated the variables that affect students' use of LMS in Saudi public universities. The study also examined the moderating impact of education and experience on the students' behavior toward LMS. 851 online surveys were submitted by students at three Saudi universities, and 833 responses were used for data analysis. The collected data were analyzed using Partial Least Squares Structural Equation Modelling along with multigroup analysis. Amongst 40 paths, the results revealed that education and experience moderated only four relationships in the proposed model. Discussions, insights and implications for decision makers in Saudi higher education are provided at the end of this paper.

CCS Concepts
• Applied computing~Learning management systems

Keywords
Technology acceptance, moderator, e-learning systems, LMS, PLS-SEM.

1. INTRODUCTION
Learning management systems (LMS) provide higher education institutions with various functionalities, including knowledge sharing, content management, discussion boards, learners' interaction and online assessment [1]. In spite of these features, the effectiveness of LMS is dependent on the students' use [2], and the advantage of its adoption is minimized if it is not used [3]. Thus, the success of LMS begins with the students' acceptance, that in turn encourages them to use the system [4, 5]. Early studies in developing countries [6, 7, 8] and Saudi Arabia [9, 10, 11, 12, 13] concluded that the utilization of LMS is still not within its full potential. Studies [14, 15, 16, 17] have found that students use only some of LMS functions, and LMS, in most cases, are utilized for only storing and downloading documents.

In terms of theory, the technology acceptance model (TAM) [18] that determines behavioral intention to use a computer system has been cited more than 40,000 times (see Figure 1). However, TAM has also been criticized [19, 20, 21] for not including moderating variables. The impact of the moderating effect on technology acceptance has been emphasized by researchers [22, 23]. Venkatesh et al. examined eight models and demonstrated that the explanatory power of six models increased after extending the models with moderators [21].

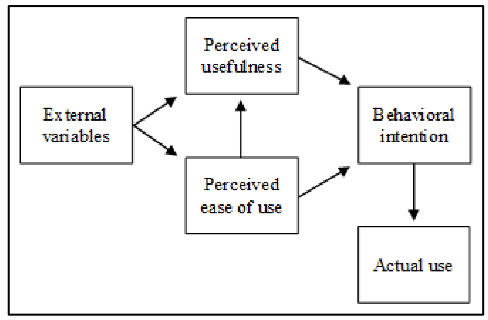

Figure 1. The TAM model [18]

From a methodological viewpoint, scholars, in most cases, postulate that the data was obtained from a homogenous population and analyze the full set of data; however, this condition is not always valid [24]. Ignoring the differences between participants may influence the validity of the findings and contribute to invalid conclusions. For example, when the path between two variables is negatively significant for undergraduate students and positively significant for postgraduates, the analysis of the full set of data may not show any significance at all.

Therefore, this study extended the TAM model with eight external factors and two demographic moderators. More specifically, this paper examines the moderating effect of education and experience on students' use of LMS in Saudi public universities.

This paper is organized as follows. Section 2 introduces the proposed model for this study. This is followed by a section on the research methodology. In section 4, the proposed model is examined using SmartPLS software. The discussion and implications sections are then presented. Finally, section 5 highlights the conclusion, limitations and future work.

2. CONCEPTUAL MODEL
The research model is depicted in Figure 2 and was mainly developed based on the TAM model [18], two moderators and eight usability variables. The eight variables were adopted from the work done by Zaharias and Poylymenakou [25], as they were carefully selected based on a profound review of many studies in the domain of usability, e-learning and educational technologies. Further, the robustness and ability of the eight variables to detect usability problems have been examined in prior studies [26, 27]. However, the direct relationships in Figure 2 between the independent and dependent variables were proposed, tested and

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discussed in the authors' prior work [28]. In this paper, the proposed model will be extended and examined with two personal moderators, namely education and experience. More details about each construct can be found in our work [28].

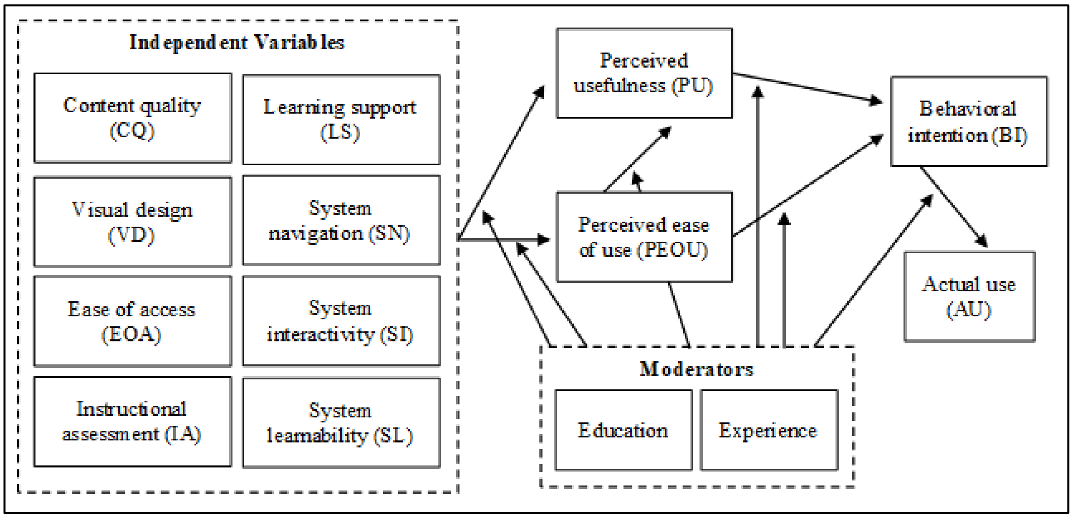

Figure 2. The proposed model

2.1 Education Level Moderating Effect

In this study, education level indicates the students' level in higher education whether undergraduate or postgraduate. Previous literature [29, 30, 31, 32, 33, 23] consider that there is a positive relationship between EDU and an individual's use of technologies. Education level was examined as an external variable that affects PEOU and PU [30, 31, 32, 33] and as a moderator that influences the relationships between the proposed variables [8, 23, 29, 34]. Therefore, the following hypotheses were proposed to examine the influence of education level.

H1(a,b,c,d,e,f,g,h): Education level moderates the effect of (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PEOU of LMS.
H2(a,b,c,d,e,f,g,h): Education level moderates the effect of (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PU of LMS.
H3(a,b): Education level moderates the effect of PEOU on students' PU and BI to use LMS.
H4: Education level moderates the effect of PU on students' BI to use LMS.
H5: Education level moderates the effect of BI on students' AU of LMS.

2.2 Experience Moderating Effect

Experience refers to someone's involvement with the investigated technology over a period of time [23]. In accordance with [20], experience in our work indicates the number of years students have been using LMS. In [35], it was argued that users make their beliefs about the target system based on their experience with it, and they will be able to assess variables (e.g. content) when gaining more experience. A variety of technology acceptance models, including A-TAM [36], determinants of PEOU [35], TAM2 [37], TAM3 [38], UTAUT [21] and UTAUT2 [39], considered that experience as a moderator plays an important role in explaining users' behavior in information systems. Because the knowledge obtained from the previous behavior will affect their intention [36]. It was stated [35] that the experience is the most used moderator in technology acceptance studies. For example, Šumak, HeričKo and PušNik conducted a meta-analysis of e-learning systems acceptance and concluded that studies usually tend to investigate the difference in causal relationships between experienced and inexperienced users [40]. Furthermore, it was emphasized [8, 34, 41, 42, 43] that experience is an important variable in students' e-learning acceptance. Therefore, the following hypotheses to investigate the effect of experience were proposed.

H6(a,b,c,d,e,f,g,h): Experience moderates the effect of (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PEOU of LMS.
H7(a,b,c,d,e,f,g,h): Experience moderates the effect of (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PU of LMS.
H8(a,b): Experience moderates the effect of PEOU on students' PU and BI to use LMS.
H9: Experience moderates the effect of PU on students' BI to use LMS.
H10: Experience moderates the effect of BI on students' AU of LMS.

3. METHODOLOGY

Our study targeted students at Saudi public universities. There are 26 public universities in Saudi Arabia with over 1.3 million students, each adopting a government-backed initiative to embed LMS as part of a strategy to learning [44]. As the study has a large and widespread population, the multi-stage cluster sampling technique was used as suggested by [45].

Regarding the instrument, this work employed online surveys for data collection. The participants selected their education level (undergraduate or postgraduate) and entered how long they have been using an LMS. For the model's variables, the students were asked to answer 52 positive statements based on a five-point Likert scale, where 1 indicates strongly disagree and 5 indicates strongly agree.

Emails were sent to 2000 students registered in three public universities. 851 responses were submitted by participants, equivalent to a response rate of 42.6%. After the preliminary examination for outliers, normality and unengaged responses, 833 responses (41.65% response rate) were used for data analysis. The sample included 560 female, 273 male, 690 undergraduate and 143 postgraduate students.

4. MODEL TESTING

This study used the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique along with multigroup analysis (MGA) and SmartPLS 3 [46] to test the proposed model. PLS-SEM is convenient for complex models and when the primary objective of the research is to extend an existing theory [47, 48]. The results obtained from the analysis are presented next.

4.1 Measurement Model Assessment

4.1.1 Education level

Table 1 and Table 2 display the results of the measurement model assessment for education groups using the PLS algorithm with 1,000 iterations using SmartPLS. The indicators' reliability is achieved when the loading of each indicator is above 0.7 [24]. The results demonstrated that all indicators were reliable except AU02 (0.50), LS04 (0.62), LS05 (0.66) and SN05 (0.67). They were therefore removed.

The constructs' reliability was done by calculating the composite reliability (CR) of each construct. The values obtained exceeded the threshold of 0.7 as suggested by [47], providing evidence of the high reliability of the constructs.

For convergent validity, this is achieved when the loading of each indicator is above 0.7 and average variance extracted (AVE) of each construct is 0.5 or above [48]. The findings showed that all AVE values were above 0.5, and therefore all constructs had adequate convergent validity.

Table 1. The measurement model assessment

	Under. Students		**Post. Students**		**Lower Experience Students**		**Higher Experience Students**	
	CR	**AVE**	**CR**	**AVE**	**CR**	**AVE**	**CR**	**AVE**
AU	0.93	0.81	0.92	0.79	0.93	0.81	0.92	0.79
BI	0.96	0.86	0.97	0.88	0.96	0.86	0.96	0.85
CQ	0.89	0.67	0.90	0.70	0.90	0.68	0.88	0.66
EOA	0.87	0.63	0.89	0.68	0.87	0.63	0.88	0.64
IA	0.94	0.80	0.95	0.82	0.94	0.80	0.94	0.80
LS	0.90	0.75	0.88	0.70	0.92	0.69	0.90	0.63
PEOU	0.94	0.79	0.93	0.77	0.94	0.80	0.93	0.77
PU	0.96	0.82	0.96	0.81	0.96	0.83	0.95	0.80
SI	0.92	0.73	0.91	0.72	0.93	0.76	0.90	0.70
SL	0.91	0.72	0.91	0.73	0.92	0.74	0.90	0.69
SN	0.92	0.75	0.90	0.70	0.92	0.75	0.91	0.72
VD	0.92	0.74	0.91	0.71	0.92	0.74	0.91	0.72

The values of the Fornell-Larcker discriminant validity for undergraduate and postgraduate students are shown in Table 2. The results indicated that the square root of each construct's AVE, presented on the diagonal line, was larger than that construct's correlation with other constructs [49]. In doing so, the measurement model assessment was successful for both sub-samples

Table 2. Fornell-Larcker discriminant validity for education level

Undergraduate Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	0.90											
BI	0.62	0.93										
CQ	0.50	0.56	0.82									
EOA	0.39	0.48	0.55	0.79								
IA	0.52	0.61	0.67	0.53	0.89							
LS	0.50	0.53	0.71	0.49	0.66	0.86						
PEOU	0.57	0.67	0.66	0.59	0.70	0.61	0.89					
PU	0.62	0.77	0.62	0.47	0.72	0.68	0.72	0.91				
SI	0.53	0.61	0.64	0.50	0.74	0.72	0.66	0.74	0.86			
SL	0.50	0.61	0.63	0.58	0.70	0.57	0.81	0.64	0.61	0.85		
SN	0.51	0.56	0.68	0.63	0.68	0.59	0.74	0.59	0.61	0.71	0.87	
VD	0.41	0.50	0.69	0.58	0.62	0.57	0.65	0.52	0.61	0.62	0.75	0.86
Postgraduate Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	0.89											
BI	0.44	0.94										
CQ	0.46	0.55	0.84									
EOA	0.34	0.55	0.57	0.82								
IA	0.38	0.49	0.61	0.55	0.91							
LS	0.42	0.45	0.67	0.53	0.64	0.84						
PEOU	0.46	0.63	0.72	0.69	0.69	0.66	0.88					
PU	0.53	0.73	0.62	0.59	0.67	0.64	0.75	0.90				
SI	0.43	0.52	0.67	0.62	0.70	0.67	0.68	0.65	0.85			
SL	0.35	0.47	0.57	0.63	0.60	0.47	0.73	0.54	0.53	0.85		
SN	0.25	0.44	0.56	0.55	0.57	0.43	0.66	0.44	0.48	0.54	0.84	
VD	0.29	0.43	0.56	0.40	0.51	0.43	0.62	0.48	0.47	0.47	0.62	0.84

4.1.2 Experience

The experience moderator variable was measured using a ratio scale, and therefore there is a need for further refinement. It was decided [50] that the median-split method is quite common in analysis and there is no strong reason preventing its use. Using median-split procedures (median = 2.0), there were 509 students within the lower experience group (median <= 2.0) and 324 students within the higher experience group (median > 2.0).

Table 1 and Table 3 display the results of the measurement model assessment for undergraduate and postgraduate students using the PLS algorithm with 1,000 iterations. As can be seen, the loadings, composite reliability, AVE and discriminant validity of each construct in both sub-samples exceeded the cut-off points. Therefore, the measurement model assessment was successful for both groups.

Table 3. Fornell-Larcker discriminant validity for experience

Lower Experience Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	0.90											
BI	0.61	0.93										
CQ	0.54	0.60	0.83									
EOA	0.41	0.52	0.59	0.79								
IA	0.53	0.65	0.68	0.54	0.90							
LS	0.53	0.56	0.72	0.50	0.68	0.87						
PEOU	0.58	0.68	0.69	0.63	0.73	0.64	0.89					
PU	0.65	0.80	0.66	0.52	0.76	0.70	0.74	0.91				
SI	0.57	0.65	0.68	0.55	0.75	0.73	0.68	0.76	0.87			
SL	0.49	0.61	0.62	0.59	0.69	0.58	0.82	0.65	0.61	0.86		
SN	0.51	0.58	0.71	0.63	0.70	0.59	0.74	0.62	0.61	0.68	0.87	
VD	0.44	0.52	0.70	0.57	0.60	0.56	0.65	0.53	0.61	0.61	0.75	0.86
Higher Experience Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	0.89											
BI	0.53	0.92										
CQ	0.42	0.48	0.81									
EOA	0.31	0.39	0.50	0.80								
IA	0.43	0.51	0.62	0.51	0.89							
LS	0.42	0.48	0.69	0.48	0.64	0.84						
PEOU	0.50	0.64	0.61	0.54	0.65	0.58	0.88					
PU	0.54	0.71	0.55	0.42	0.63	0.65	0.69	0.90				
SI	0.40	0.54	0.59	0.45	0.72	0.69	0.63	0.67	0.83			
SL	0.43	0.56	0.63	0.57	0.68	0.56	0.75	0.59	0.57	0.83		
SN	0.39	0.46	0.59	0.58	0.61	0.56	0.70	0.48	0.55	0.68	0.85	
VD	0.29	0.40	0.63	0.50	0.60	0.56	0.63	0.47	0.54	0.58	0.69	0.85

4.2 Structural Model Assessment

Table 4 and 5 show the results of path analysis and the explained variance (R^2) of the pooled sample and the two sub-samples beside the test of differences between the sub-samples. First, the bootstrapping technique was used with 10,000 sub-samples for a path coefficients test, as recommended by [47]. Then, the statistically significant differences between the two sub-samples were examined. Unlike the liberal parametric test and the one-tailed PLS-MGA, the permutation test is non-parametric, two-tailed, more conservative and recommended by [47, 51]. Therefore, the permutation test was employed for this study and run with 5,000 permutations and a two-tailed option at a 0.05 significance level, as recommended by [51]. The results showed that education moderated two paths between SL → PEOU and BI → AU. In the case of experience, two paths were moderated amongst the model relationships, IA → PU and PU → BI.

Table 4. The moderating effect for education

Path	Undergraduates		Postgraduates		Test
	β	R^2	β	R^2	
CQ → PEOU	0.04	0.73	0.14^{**}	0.76	-0.10

Path	Undergraduates		Postgraduates		Test
	β	R^2	β	R^2	
LS → PEOU	0.02		0.15^{**}		-0.13
VD → PEOU	0.04		0.15^{**}		-0.10
SN → PEOU	0.19^{***}		0.12^{*}		0.07
EOA → PEOU	0.05		0.15^{*}		-0.11
SI → PEOU	0.13^{***}		0.06		0.07
IA → PEOU	0.05		0.08		-0.02
SL → PEOU	0.47^{***}		0.27^{***}		0.20^{*}
CQ → PU	0.05	0.68	0.05	0.63	-0.00
LS → PEOU	0.18^{***}		0.10		0.09
VD → PU	-0.12^{**}		0.05		-0.17
SN → PU	-0.04		-0.18^{*}		0.14
EOA → PU	-0.02		0.13		-0.15
SI → PU	0.28^{***}		0.08		0.20
IA → PU	0.22^{***}		0.24^{**}		-0.02
SL → PU	0.03		-0.10		0.12
PEOU → PU	0.33^{***}		0.50^{***}		-0.17
PEOU → BI	0.25^{***}	0.63	0.19^{*}	0.54	0.05
PU → BI	0.60^{***}		0.58^{***}		0.02
BI → AU	0.62^{***}	0.38	0.44^{***}	0.19	0.17^{*}

Table 5. The moderating effect for experience

Path	Lower Exp.		Higher Exp.		Test
	β	R^2	β	R^2	
CQ → PEOU	0.08*	0.77	0.04	0.66	0.04
LS → PEOU	0.05		0.04		0.01
VD → PEOU	0.02		0.11*		-0.10
SN → PEOU	0.16***		0.19***		-0.03
EOA → PEOU	0.07*		0.04		0.03
SI → PEOU	0.10*		0.16**		-0.06
IA → PEOU	0.08*		0.03		0.05
SL → PEOU	0.47***		0.37***		0.10
CQ → PU	0.08*	0.70	0.04	0.60	0.04
LS → PEOU	0.13**		0.22***		-0.09
VD → PU	-0.12**		-0.06		-0.06
SN → PU	-0.02		-0.16**		0.14
EOA → PU	-0.02		-0.01		-0.01
SI → PU	0.30***		0.24***		0.05
IA → PU	0.28***		0.12*		0.16*
SL → PU	-0.002		0.07		-0.07
PEOU → PU	0.30***		0.41***		-0.11
PEOU → BI	0.19***	0.66	0.30***	0.54	-0.11
PU → BI	0.66***		0.50***		0.16*
BI → AU	0.61***	0.37	0.53***	0.28	0.08

*** p<.001, ** p<.01, * p<.05

5. DISCUSSION

5.1 Education

The results of the path testing for undergraduate and postgraduate students are presented in Table 4. Consistent with [8] in LMS, the findings indicated that the proposed model explained more variance in the undergraduate students' model compared to postgraduate students, meaning a better model fit for undergraduate students in the dependent variables especially for AU.

Compared to undergraduate students, postgraduate students had more statistically significant relationships, indicating that the proposed model might be more important for postgraduates. Amongst the independent variables, the highest significant path in the two models was between SL and PEOU, this means that when LMS are easy to learn, students regardless of their education level are more likely to use the system. Therefore, universities should ensure that the adopted LMS have a high degree of learnability in order to motive students to use them. The weakest significant path was SI → PEOU for undergraduates and SN → PEOU for postgraduates. This implies that although interactions and system navigation exist to support the perceived ease of use of LMS, their importance is weak compared to the other independent factors. In terms of postgraduate students, the relationship between PU and BI was the strongest across the other relationships, consistent with past literature [18, 20]. Meaning that postgraduates' intention to use LMS was driven, to a large extent, by the usefulness and functionality provided by the system. This result suggests more consideration should be dedicated to the functionality provided by the system when dealing with postgraduate students.

Using MGA analysis, it was found that undergraduate and postgraduate students are significantly different in two paths SL → PEOU and BI → AU, and the two moderated relationships were stronger for undergraduates. Our results were expected because people with less education would perceive new technologies arduous and difficult to learn and therefore their decision to use e-learning systems will depend on the easiness of the technology [32, 52]. Past studies [30, 33, 52] suggested that users with less education are associated with computer anxiety that causes lower computer self-efficacy, which could contribute to lowering ease of use perceptions. Further, Sun and Zhang argued that those who have higher education possess a greater ability to understand the value of a new technology, accept it and use it [23]. Therefore, the hypotheses that education has a significant effect on SL → PEOU (H1h) and BI → AU (H5) were accepted.

5.2 Experience

The findings of the hypotheses' testing for lower and higher experience students are presented in Table 5. In accordance with [36, 38], the results demonstrated that the proposed model explained more variance in the students with lower levels of experience, so the LMS usage of less experienced students was better predicted by the independent variables.

Regarding the proposed paths, less experienced students had more significant relationships than those who have higher levels of experience with LMS, indicating that the proposed model might be more important for less experienced students. Amongst the independent variables, the highest significant path for both groups was SL → PEOU followed by SI → PU, implying that PEOU is strongly driven by SL and PU by SI which will, in turn, contribute to the students' use of LMS. Similar to the TAM model [18], PU → BI was the strongest relationship for less experienced students. This means that students with lower experience were significantly motivated by the usefulness of LMS, indicating special attention should be given to the expected performance of LMS when working with less experienced students. The least significant paths were EOA → PEOU for less experienced students and VD → PEOU for higher experience students. This implies that although providing LMS with attractive visual design and designing it to be easy to access is necessary in the students' use of LMS, its effect on the students' perceived ease of use of LMS is limited compared to the other independent factors.

Contrary to [21] and [8] in Lebanon, the test of the moderating effect revealed that the students' experience with LMS moderates the relationship between PU and BI. Although Tarhini et al. demonstrated the effect of PU and BI is stronger for higher experience students in Lebanon [34], the path PU → BI in our study was stronger for less experienced students, consistent with previous literature in information systems [18, 36] and e-learning [52, 43]. In [53], it was assumed that more highly experienced users are more concerned about enjoyment, that consequently reduces the effect of perceived usefulness. The result indicated that less experienced students are more influenced when an LMS enabled them to achieve tasks more quickly and learn effectively, which in turn increases their intention to use LMS. Thus, the usefulness of the system should be treated carefully when dealing with less experienced students.

For IA → PU, the MGA analysis revealed that this relationship was moderated by LMS experience. More specifically, the effect was stronger for less experienced compared to more experienced students. Further, the impact of IA on PU was significant in both groups, but higher in the less experienced students' model. This implies that students with less experience are more influenced when LMS have good self-assessment tools that help them understand the content of courses which, in turn, makes them perceive LMS useful in their education. Moreover, the effect of IA will be extended to affect the less experienced students' intention to use LMS, as the relationship between PU and BI was stronger for less experienced students. Therefore, the findings suggested accepting the hypotheses H9, experience moderates the effect of PU on BI to use LMS, and H7g, experience moderates the effect of IA on students' PU of LMS.

6. IMPLICATIONS

The results have practical and theoretical implications. We examined the impact of eight external factors on students' utilization of LMS in Saudi higher education. Understanding the impact of these factors is vital for decision makers, system developers, course designers and teachers to implement effective policies and strategies that are designed to increase the students' use of LMS in Saudi public universities. In this manner, leaders in Saudi higher education ought to guarantee that the utilized LMS mirrors the adjusted factors in the proposed model sufficiently.

Furthermore, our investigation is one of the few studies that shed light on the differences between undergraduate, postgraduate, inexperienced and experienced students in the e-learning acceptance. Our work estimated that the students' education and experience could indirectly affect their use of LMS by moderating the relationships between the independent and dependent constructs. A consideration of the moderating effect of education and experience might enlighten decision makers on use of LMS amongst different groups of students. Consequently, this would help to design strategies for each student's segment, thus increasing the chance of using LMS.

From a theoretical viewpoint, this study demonstrated the TAM model in the acceptance of LMS in Saudi public universities. Although the students' experience moderating effect in Saudi LMS using the TAM3 model was examined [42], our study is unique: the usual version of TAM [18], has been adapted to give it extra external variables and demographic characteristics, which were used as moderators in the proposed model. Moreover, this paper has addressed the criticism concerning the lack of moderating variables in TAM. It has also provided evidence of the moderating effect of demographic variables.

Regarding the research methodology, this study is so far one of the few studies in e-learning acceptance that benefits from using the multi-stage cluster sampling technique. The convenience sampling technique is currently dominant in quantitative technology acceptance. Secondly, PLS-SEM was used to statistically examine the relationships between the proposed variables, which is more appropriate for complex models, as argued by [24, 54]. The moderating effect of education and experience is currently poorly understood [8]. Our investigation has included these variables using MGA analysis.

7. CONCLUSION AND LIMITATIONS

This paper provided solutions for the problems addressed in the introduction section by extending the TAM model with eight external variables and two moderators. Our research primarily investigated the moderating effect of education and experience on the students' use of LMS in Saudi higher education. This work should therefore be of interest to researchers, academics, decision makers, teachers and LMS designers concerned about the students' acceptance, adoption or use of e-learning systems in universities.

This study investigated the moderating effect of education and experience on 40 relationships and found that two relationships were impacted by education (SL → PEOU and BI → AU) and two relationships were affected by experience (IA → PU and PU → BI). This led us to conclude that the two demographic moderators have very little effect on the use of LMS in Saudi public universities. We therefore suggest that Saudi universities should in general utilize similar policies to prompt students toward using LMS. However, consideration should be given to system interaction for undergraduates and content quality, visual design and ease of access for postgraduates. On the other hand, content quality and ease of access is more relevant to those students with less experience compared to more experienced students.

This study has some limitations. This paper focused on students at Saudi public universities, and their views may be not quite the same as students at Saudi private institutions. Consequently, different investigations could focus on students at both public and private institutions. Additionally, our study examined the moderating impact of education and experience, and future work could subsequently include other demographic moderators (e.g. academic performance) or social moderators (e.g. language). Finally, the present research examined only student perceptions. Additional research could explore the perspectives of educators and representatives in Saudi higher education.

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