FACTORS AFFECTING UNDERGRADUATES' BEHAVIORAL INTENTION TO USE LEARNING MANAGEMENT SYSTEMS

Fatma Jaupi, University of Tirana
Rezart Prifti, University of Tirana

ABSTRACT

The purpose of this paper is to analyze factors that affect the behavioral intentions of undergraduate students to use blended learning methods. The research uses the three-tier use model (3-TUM) to explore the influencing behavioral factors of students at the undergraduate level to use LMSs. *The research was carried out at a university and consisted of undergraduate students majoring in business-related fields. Students responded to online questionnaires administered at the end of the semester concerning their experience with the LMS. A customized Moodle platform was used to measure the user's perceived usefulness, perceived satisfaction, and perceived ease of use with the LMS.* Results show that interactivity in portal and self-efficacy have a direct impact on all second-tier constructs, while multimedia instruction influences only perceived usefulness and perceived satisfaction. In addition, perceived usefulness impacts perceived satisfaction. Perceived usefulness and perceived ease of use significantly impact behavioral intention of students to use learning platforms, while the relation between perceived satisfaction and behavioral intention was unindicative. *The study confirms that the individual experience of users and the quality of the system affect the successful implementation of an LMS and its adoption by users.*

Keywords: *behavioral intention, blended learning, learning management systems, 3-TUM.*

INTRODUCTION

In the recent emerging technological environment, the application of information and communication technology is affecting the broad scope of the education and learning environment by introducing new techniques and tools as facilitators to the educational process (Shoikova et al., 2017, 2018; Zhu et al., 2016) Previously, evolutionary changes in education were mainly attributed to factors related to globalization, the shift toward information knowledge-based economies, and the changing nature of work (Shoikova et al., 2017). The sudden new reality of the Covid-19 pandemic made it imperative to find new ways to manage the measures imposed by governments throughout the world that stressed technology as the way to deliver education. The application of technology is altering how education is conceptualized, through the introduction of new methods of smart learning (Bajaj & Sharma, 2018; Demir, 2021). Furthermore, to be successful in the work environment, which is becoming more digitized, a learning environment enhanced by internet tools, namely elearning, could be of great use for the young generation.

LITERATURE REVIEW

It is necessary to first define elearning as a crucial component of smart education and to estimate the benefits of using it in the fast-paced, changing environment. Our research aims to understand learning management systems and then to investigate drivers such as behavioral intent that influence the students (i.e., learners) to engage in the use of these systems during their learning process and their intention of re-using them in a different period. This serves as the research question of this study.

Bajaj and Sharma (2018) defined smart education as "providing personalized learning, anywhere and anytime" (p. 835), thus proposing the adaptive education model as a tool. Zhu et al. (2016) stated that the quality improvement of lifelong learners' learning is the main objective of smart education, while Shoikova et al. (2017) clearly emphasized the use of high-level technology as the interlocutor between teachers, students, and other learning partners in smart education to stimulate creativity, collaboration, and multimedia productivity.

In the simplest form, elearning is defined by Raab et al. (2001) as a form of distance learning, where teachers and students are placed in different places and times during the teaching and learning process (see also Amsal et al., 2021). Clark and Mayer (2012) defined the golden circle in the context of elearning by defining elearning as training delivered on digital devices, including content, i.e., information, as well as instructional methods ("what?"), intended to support individual learning or group performance goals ("how and why?"). Kocur and Košč̌ (2009) gave a very flexible scope of elearning in their SWOT (strengths, weaknesses, opportunities, and threats) analysis by exploring the different benefits of elearning, such as the availability on the internet, the interactivity and multimedia resources, the enhancement of independence, creativity, and their own study style, as well as the possibility of national and international exchange of teacher experiences. Bouhnik and Marcus, cited by Amsal et al. (2021), linked the increased usage of elearning in universities with the benefits associated with these systems, namely the freedom in determining lessons, provision of independence from lecturers, ease in expressing thoughts and opinions, and ease of obtaining materials. Moreover, Garrison (2016) explained how the two primary applications that constitute elearning are online and blended learning, with the latter shedding the focus on program design. This is also supported in the smart education model developed by Demir (2021), where educators, as one of the major system's components, should not only be effective technology users but should also offer technical support to the learners in the form of direct instruction.

Regarding the study of Bhuasiri et al. (2012), which intended to identify factors influencing elearning success for ICT experts and faculty in the scope of a developing country, the strongest pillars were technology awareness, enhancing technical knowledge and skills, and providing a high level of university support. et al. (2015) identified a total of five challenges that teachers are faced with while being integrated into an elearning environment: learning style of students and cultural challenges, pedagogic elearning challenges, technological challenges, technical training challenges, and time management. Alqahtani and Rajkhan (2020) observed how the most significant factor during the COVID-19 pandemic was readiness for elearning implementation, expressed through the following characteristics: technology knowledge management, support from management, increased student awareness of utilizing elearning systems, and demanding a high level of information technology from the instructors, students, and universities.

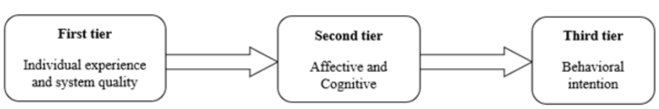
A very common tool used to implement elearning in universities is a Learning Management System (LMS) such as MOODLE, Blackboard, and others. An LMS is a web-based software application that is designed to handle learning content, student interaction, assessment tools and reports of learning progress, and student activities (Mohd Kasim & Khalid, 2016). In 2011, Liaw and Huang (2011) described the elearning landscape through four characteristics: the multimedia environment, the self-learning process, the information networking, and the cross-platform environment, which all enhance the benefits the participants gain from these platforms. To be able to properly incorporate elearning platforms in the university, it is very important to understand the key success factors of its implementation. There are various reasons why an LMS adaptation is either beneficial to the university stakeholders or not. Characteristics, such as identified technology, instructor and participants' characteristics, and previous use of technology, are crucial when choosing the right platform for a university (Volery & Lord, 2000). Several authors (Alhabeeb et al., 2018; Selim, 2007; Valsamidis et al., 2016) also added university support to the abovementioned factors.

Nevertheless, the successful implementation of an elearning system depends not only on technology-related factors but on human ones as well. According to Eom and Ashill (2016), elearning systems are a form of information system incorporating human and nonhuman aspects, and as such, various factors should be considered during the analysis (see also Al-Adwan et al., 2021). Success in the utilization of an information system is measured using two main pillars of research. The first is the Technology Acceptance Model (TAM), derived from interdisciplinary models such as the unified theory of acceptance and use of technology and the theory of planned behavior developed by Davis and Venkatesh (2004) and Venkatesh and Davis (2000). The second is the expectation confirmation model developed by Al-Adwan et al. (2021), Baleghi-Zadeh et al. (2017), and Bhattacherjee (2001).

THREE-TIER USE MODEL

To examine the relationship between the factors that influence the use and adoption of blended learning, we applied a framework introduced by Liaw et al. (2007) named the three-tier use model (3-TUM). This theoretical framework aims to explain user perceptions on the acceptance of behavioral intentions to use new technology and to find why learners are dissatisfied with elearning experiences. The three tiers of the framework presented in Figure 1 are (a) Individual experiences and system quality, (b) affective and cognitive reactions, and (c) behavioral intention.

Figure 1.
The Three-Tier Use Model (3-TUM) (Liaw, 2007)



The model we used is based on conceptual work found in Liaw et al. (2007), Liaw and Huang (2016) and Liaw (2004). They suggest four elements to be considered when building elearning ecosystems: environmental characteristics, environmental satisfaction, learning activities, and learners' characteristics. In addition, for more effective systems Liaw et al. (2007) suggested three factorial considerations: learner characteristics, instructional structure, and interaction. Each factorial tier is made up of subfactors. For example, learner characteristics is made up of self-efficacy, self-directed behavior, and autonomy. Each factor has a similar breakdown of subfactors measured through a structured questionnaire in all environments giving a comprehensive understanding of how individual behavioral attitudes predict technology adaptivity. We used this model for two main reasons. First, it better grasps the context of elearning evolution from technical systems and digital content to interactive content. Second, the methodology is superior to any other model based on the logical flow that integrates different perspectives from different disciplines such as motivation, social cognitive theory, theory of planned behavior, technology acceptance model, etc.

Based on the literature review and the selection of the three-tier use model (3-TUM), we formulated the following hypotheses to investigate the factors that incentivize the learners into using the LMS and how this experience affects their behavioral intent to use them again:

H1: The individual experience and the quality of the used LMS have a significant direct positive effect on the affective and cognitive aspects of the LMS, resulting in higher perceived usefulness, satisfaction, and ease of use.

H2: The affective and cognitive aspects, i.e., the perceived usefulness, satisfaction, and ease of use, have a significant direct positive effect on the learners' behavioral intention to use the LMS for the second time.

METHODOLOGY AND DATA ANALYSIS

The research was carried out at our university, and the sample consisted of undergraduate students majoring in business-related fields. The questionnaires were administered online where students answered the respective questions at the end of the semester based on their experience with the LMS. To measure the user's perceived usefulness, satisfaction, and ease of use, we used a highly customized Moodle platform. The students, apart from their face-to-face learning, were offered complementary online courses in which they could participate once a week to obtain further learning information through video infographics, online assignments, and quizzes. This learning methodology was introduced during one semester and consisted of 2 hours per week for 15 weeks total. The LMS was a highly customized platform based on instructional design principles for learning purposes. It had many learning measurements tools from simple tests to interactive digital content and peer review modules that make the platform more engaging. In addition, it had a pointing system for users to keep track of their performance for selected courses that they took.

The study participants were selected by simple random sampling. The platform has been running for four years on several course subjects at our university. Each year, at least 200 students participated in the course. At the end of every semester we sent out a questionnaire to all of the students explaining the purpose of the research. The individuals willing to participate in this study were given a brief explanation of the study, its purpose, and the outcome of the validation process. At the end of the data collection process, the total number of participants was 1,021 students (from a total of around 8,000), majoring in the following fields: Business Administration (n = 568: 55.5%), Finance (n = 356: 35%), Business Informatics (n = 87; 8.5%), and Economics (n = 10; 1%). Out of the total number of participants, 186 were male (almost 18%) and 835 were female (almost 82%), none of which reported a previous experience with an LMS. The distribution of participants in the questionnaire is presented in Table 1.

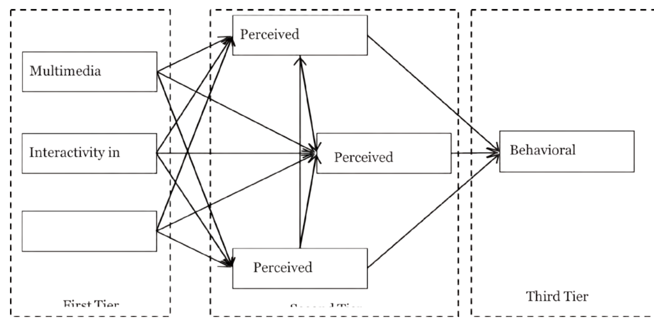
Table 1.
Number of Participants Based on Their Year of Study, Disaggregated by Gender

Students' year of study	Female	Male
I	518	123
II	9	1
III	308	62
Total	835 (i.e., 82%)	186 (i.e., 18%)

The data collection was conducted through an online, five-point, Likert-type questionnaire (Cigdem & Ozturk, 2016; Huang & Liaw, 2018; Liaw, 2008; Liaw & Huang, 2013) based on a reaction scale from 5 (*strongly agree*) to 1 (*strongly disagree*), according to the following constructs: Multimedia Instruction (UM), Interactivity in Portal (IP), LMS Self-efficacy (LM), Perceived Usefulness (DM), Perceived Satisfaction (KM), Perceived Ease of Use (SP), and Behavioral Intention (LP).

Liaw (2007) argued that the use of the 3-tier model is adequate when conducting research regarding faculty and staff behaviour towards computers and the internet, thus this study, based on this conceptual framework, tries to understand the relationship between the students' behavioural intention to use LMS and selected factors such self-efficacy, multimedia instruction, interactivity, perceived usefulness, and perceived ease of use (see Figure 2).

Figure 2.
Theoretical Framework of the Study



At first, we tried to understand how the individual experience of using the system and its quality, such as multimedia instruction, interactivity in the portal and systems' self-efficacy, affected the students' perceived usefulness, satisfaction, and ease of use. Then, we investigated if the above-mentioned perceptions on the online learning platform influence the students' behaviour in using the platform for a second time. Ever since the model was originally proposed, it has been used and/or further developed in various research studies (such as Al-Rahmi et al., 2015; Cigdem & Ozturk, 2016; Garcia, 2017; Nurkaliza, 2014).

Data collected from the questionnaire were analyzed through the exploratory factor analysis (EFA) and the confirmatory factor analysis (CFA), thus testing the structural validity of the questionnaire. In a CFA, a tool undergoes assessments for dimensionality, validity, and reliability, in which dimensionality is achieved when all the items have a factor loading of more than 0.5 (Black et al., 2006).

Table 2 presents the questions of the survey filled by the participants of the study, distributed according to each construct and their respective mean and standard deviation.

Table 2.
Distribution of Surveyed Items to Constructs Structure

Construct	Item code	Item	Mean	Std. deviation
Multimedia Instruction	UM1	I like to use video media instruction in Portal	3.85	1.110
	UM2	I like to use multimedia instruction in Portal	3.87	1.063
	UM3	I like to use presentations/slides in Portal	4.52	.836
Interactivity in Portal	IP1	I would like to share my elearning experience	4.31	.974
	IP2	I believe Portal can assist teacher-learner interaction	4.10	1.068
	IP3	I believe Portal system can assist learner-learner interaction	3.85	1.176
LMS Self-efficacy	LM1	I feel confident using Portal	4.35	.903
	LM2	I feel confident operating functions of Portal	4.24	.883
	LM3	I feel confident using contents of Portal	4.54	.759
Perceived Usefulness	DM1	Using Portal gives me greater control over my work	3.99	.981
	DM2	Using Portal improves my performance	4.08	1.012
	DM3	Using Portal makes it easier to do my job	4.15	.989
	DM4	I believe Portal contents are useful	4.44	.816
Perceived Satisfaction	KM1	I am satisfied with using Portal as a learning assisted tool	4.39	.870
	KM2	I am satisfied with using functions of Portal	4.24	.898
	KM3	I am satisfied with multimedia instruction in Portal	4.10	.970
	KM4	I am satisfied with interactivity in Portal	4.07	.967
Perceived Ease of Use	LP1	Learning to operate portal system would be easy for me	4.28	.951
	LP2	I would find it easy to get Portal to do what I want it to do	4.30	.951
	LP3	I would find the system easy to use	4.30	.952
Behavioral Intention	SP1	I intend to use Portal to assist my learning	4.29	.953
	SP2	I intend to use functions of Portal to assist my learning	4.22	.963
	SP3	I intend to use Portal as an autonomous learning tool	3.87	1.115
	SP4	I would like to see Portal functions implemented further in departmental modules	4.19	1.063

To determine the internal consistency of the questionnaire and test the reliability of the created variables (i.e., to see whether the items that were summed to create each factor formed a reliable scale), we computed Cronbach's alpha for the subscales within the questionnaire.

The alpha for the subscales ranged from .768 to .901. All the values revealed reasonable levels of reliability. Besides Cronbach's alpha, composite reliability (CR) is used in assessing the reliability of a set of indicators. Based on literature findings, the threshold value must be higher than 0.70 (Polit et al., 2007). Based on the results obtained from the reliability tests, shown in Table 3, all CRs are above 0.70 (Ab Hamid et al., 2017; Nusair & Hua, 2010). The lowest value obtained was 0.799 for Multimedia

Table 3.
Results of Reliability Test

Constructs	Cronbach's alpha	AVE	CR
UM	0.768	0.59	0.80
IP	0.808	0.59	0.81
LM	0.850	0.66	0.86
DM	0.886	0.43	0.88
KM	0.895	0.62	0.83
LP	0.901	0.73	0.89
SP	0.849	0.48	0.89

Instruction. However, the values were still in an acceptable range. Since both values meet the specification, the measurement instrument of this study was considered reliable. For validity purposes, we calculated the average variance extracted (AVE). The average variance extracted (AVE) was greater than 0.5, indicating that the measurement questions can better reflect the characteristics of each research variable in the model (Ab Hamid et al., 2017; Hulland, 1999; Nusair & Hua, 2010). Composite reliability was above 0.70 for all the variables in this study. Moreover, AVE was above 0.50 for most of the constructs, which denotes that the latent variables had a convergence ability that is quite ideal.

Table 4.
Factor Analysis

	Initial Eigenvalues		Extraction Sums of Squared Loadings
Component	**Total**	**% of Variance**	**Cumulative %**
1	12.084	50.351	50.351
2	1.562	6.508	56.859
3	1.344	5.599	62.458
4	1.155	4.812	67.270

The structure of the constructs was tested using an exploratory factor analysis (EFA). We also conducted Bartlett's test of sphericity to verify if the structure of factors was relevant based on the data obtained. Table 5 shows the values of the sphericity test at x2 (276) = 18014.698 (p < .001), which supports the fact that the structure is relevant. Kaiser-Meyer-Olkin was found to be 0.952 which is higher than the minimum sample size required for factor analysis (0.5) (Field, 2009). The results of the exploratory factor analysis generated four different factors, explaining 67.27% of the total variance, in comparison to the initial hypothesis that proposed seven factors. Table 6 presents the new structure, distribution of items, and their loading toward each factor.

Table 5.
Kaiser-Meyer-Olkin and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**.952**
Bartlett's Test of Sphericity	**Approx. wChi-Square**	**18014.698**
	df	276
	Sig.	.000

Table 6.
Pattern Matrix

Item	Factor			
	1	**2**	**3**	**4**
UM1				.973
UM2				.951
UM3	.275	.165		260
IP1	.706			
IP2	.933	−.123	−.117	
IP3	.911	−.229		
LM1		.952		
LM2	−.208	.969		
LM3		.852		
DM1	.715	.138		
DM2	.818			
DM3	.792			
DM4	.682	.159		
KM1	.542	.432		
KM2	.373	.532		
KM3	.210	.335		.361
KM4	.320	.389		.207
LP1			.895	
LP2			.928	
LP3			.919	
SP1	.709		.254	
SP2	.703		.190	
SP3	.694	−.208		.127

Confirmatory factor analysis (CFA) was used to assess the measurement model in terms of convergent validity and discriminant validity. We also assessed convergent validity, Average Variance Extracted (AVE), and Composite Reliability (CR). Each observed variable must load its latent variable with at least 0.7 to provide adequate convergent validity (Hair et al., 2015). PEOU9, PEOU10, and ENJ6 did not have an adequate load on the related latent variables and therefore they were extracted from the dataset. Since the loadings of PEOU4, SN1, and SN5 were only slightly lower than 0.7, they were not excluded. For internal consistency, the AVE value should be higher than 0.5 and the CR value should be 0.7 or higher for each latent variable (Hair et al., 2015). Considering the AVE and CR values, the dataset had adequate convergent validity. In the CFA, the 24 items were analyzed according to the constructs mentioned in the theoretical framework. The model was analyzed step-by-step until the fitness of the model was confirmed. All 24 items in Model 1 were included in the first modelling analysis. Based on the results, the construct validity was acceptable and based on the values provided in Table 7 the fitness of the model is within statistical criteria.

Table 7.
Fitness of the Model

	CFI	RMSEA
	>0.9	<0.08
Fitness	0.905	0.084

CFI: comparative fit index; RMSEA: root mean square of error approximation

RESULTS

The first constructs under investigation were Multimedia Instruction (UM), Interactivity in the Portal (IP), and LMS Self-efficacy (LM). All tier 1 constructs, except Multimedia Instruction, exerted a direct influence on Perceived Ease of Use (LP), Perceived Usefulness (DM), and Perceived Satisfaction (KM).

Compared to other tier 1 constructs, multimedia instruction had a weaker correlation to tier 2 constructs, and based on the value of standardized coefficients, it did not significantly affect users' Perceived Ease of Use. Such a result indicates that students find multimedia beneficial and functional to use for learning purposes but might not be satisfied with the practicality of additional online learning information and the structure of assignments or quizzes. System administrators should pay close attention to the needs of students in making this component of the portal easier to learn and/or use.

Interactivity in the portal is shown to strongly affect all tier 2 constructs, Perceived Usefulness being the one with the highest correlation among others. Such correlation between constructs suggests that the way the system assists teacher-student and student-student interaction positively affects the belief that the portal enhances learning productivity, satisfaction from the added-value of the portal, and the easiness students perceive when using the portal. This is consistent with Cidral et al. (2018) and Eom and Ashill (2016), which show that the more meaningful interaction there is, the higher the user satisfaction. When studied by Baleghi-Zadeh et al. (2017), the interactions had a significant effect on perceived usefulness, while Binaymin et al. (2019) observed the significance of interactivity in users' perceived ease of use and usefulness.

Lastly, LMS Self-efficacy, based on the standardized coefficients, presented a high influence on all tier 2 constructs, with Perceived Ease of Use being the one more positively impacted. The correlation between the constructs suggests that students' self-reliance on using the system positively affects their perceived practical use of the portal, productivity, and satisfaction. As such, it directly influences perceived satisfaction and ease of use. This is further supported by Al-Gahtani (2016), Huang and Liaw (2018), and Park (2009), whose results showed how self-efficacy could be a predictor of perceived ease of use and usefulness.

After we investigated how the individual experience and the system quality affected the students' reaction to the learning experience, we analyzed if these reactions would influence the behavior of students to use the blended learning method again.

As observed in Table 8, Perceived Ease of Use positively affects Perceived Usefulness and Behavioral Intention, while the influence on Perceived Satisfaction was not statistically significant. The relationship between the constructs suggests that students believe that a practical and simple-to-use system affects the perceived level of usefulness and increases their intention in using the system to their benefit. This is consistent with the results from Venkatesh and Davis (1996), which shows a direct perceived impact in the ease of use on the intention to use the system. Further supported by Humida et al. (2022), Khan et al. (2020), and Liaw and Huang (2013), which showed how perceived ease of use of search engines can be considered a predictor of individual perceived usefulness of search engines, leading to a prediction of individual intention to use search engines. Mohammadi (2015), Salloum et al. (2021), and Šumak et al. (2011) found no effect of perceived ease of use on behavioral intention, but they did find that it indirectly impacts behavioral intention by significantly affecting perceived usefulness.

Users' perceived satisfaction, also defined as users' global emotional response to the cognitive appraisal of the value of the IT service (Sun et al., 2012), marks one of the factors that could predict

Table 8.
Regression Weights

			Estimate (unst.)	S.E.	C.R.	P	Label	Estimate (std.)
LP	<---	UM	.075	.023	3.248	.09	par_20	.098
LP	<---	IP	.259	.033	7.913	***	par_23	.268
LP	<---	LM	.413	.033	12.656	***	par_26	.439
DM	<---	UM	.082	.016	5.009	***	par_18	.117
DM	<---	IP	.618	.035	17.668	***	par_21	.696
DM	<---	LM	.316	.027	11.757	***	par_24	.365
DM	<---	LP	.128	.028	4.573	***	par_30	.139
KM	<---	UM	.117	.016	7.140	***	par_19	.176
KM	<---	IP	.276	.049	5.650	***	par_22	.330
KM	<---	LM	.330	.033	10.027	***	par_25	.405
KM	<---	LP	.071	.026	2.787	.05	par_31	.082
KM	<---	DM	.279	.063	4.435	***	par_32	.296
SP	<---	DM	.791	.060	13.171	***	par_27	.670
SP	<---	KM	.125	.058	2.156	.07	par_28	.100
SP	<---	LP	.159	.031	5.051	***	par_29	.146

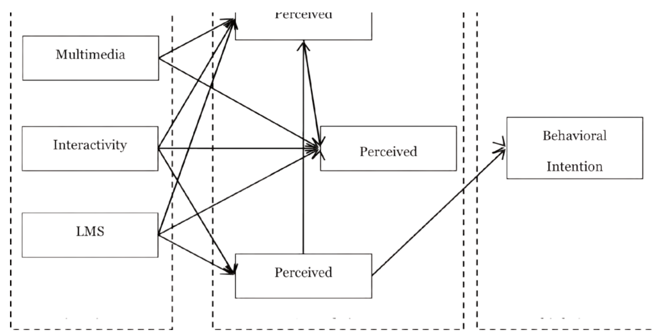
*A more detailed table regarding regression weights is presented on Annex 1.

the intention of use of elearning platforms. As observed from the results of our confirmatory factor analysis, Perceived Satisfaction, while being positively affected by Perceived Usefulness, does not directly impact the user's Behavioral Intention. Such findings are consistent with those of Joo et al. (2018), who observed how perceived usefulness had a positive impact on perceived satisfaction, but are inconsistent with several studies that provide a direct relationship between satisfaction and behavioral intention to use elearning technology (del Barrio-García & Arquero, 2015; Cigdem & Ozturk, 2016; Lee, 2010; Liaw, 2008).

The results of our analysis show that perceived usefulness is the construct with the most significant influence on the user's behavioral intention, and as such, the perceived enhancement of productivity that a system facilitates directly affects the intention to use it. This finding is consistent with various studies (Agudo-Peregrina et al., 2014; Al-Gahtani, 2016; Huang & Liaw, 2018; Salloum et al., 2021; Tarhini et al., 2014) that confirm how perceived usefulness has one of the most direct impacts on behavioral intention.

Based on the analysis of the constructs, the model derived from our findings is presented below:

Figure 3.
Derived Model for Students' Behavioral Intention to Use LMS



DISCUSSION

We used the three-tier use model (3-TUM) for testing the factors that contributed to the use and satisfaction of a chosen LMS by learners and that affected the behavioral intent of these users to use the system again at another time, through the application of two hypotheses. Our analysis and results showed that not all the components of the first tier had a significant positive effect on the components of the second tier. The relation between the first tier's component, Multimedia Instruction, with the second tier's component, Perceived Ease of Use, turned out to be weak, leading to the conclusion that system administrators should take into account the needs of system users and make their interaction with the system and the system itself easier to learn and use. On the other hand, the Interactivity in the Portal component resulted in a strong influence on the Perceived Usefulness of the system, while LMS Self-efficacy strongly affected all three components of the second tier, being in line with the conclusions and suggestions of the literature and other researchers.

The second hypothesis intended to investigate whether the affective and cognitive factors would affect the behavioral intention of students to use the system for a second time. Out of the three components, Perceived Usefulness, Perceived Satisfaction, and Perceived Ease of Use, the second one did not have a significant positive effect on the Behavioral Intention of students to reuse the system, while the first one strongly affected the third-tier factor. The results are in line with other studies, indicating the strong impact that the system's perceived usefulness to the students has on their intent to use the system for a second time.

CONCLUSION

The study confirms the effects that the individual experience of users and the system quality have on the successful implementation of an LMS and its adoption and postadoption by the users. This is in line with various models developed mainly in the first stream of research, but the 3-TUM approach and the aforementioned models do not take into consideration how the factors and the use of a specific chosen LMS affect and are related to the learning outcomes and performance of the learners, i.e., the students using such a system. Therefore, it is important for other scholars to continue this research and to conduct further studies through the use of integrated models to address this limitation.

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