MOODLE'S TECHNOLOGY ACCEPTANCE MODEL IN HIGHER EDUCATION: ANALYSIS OF PREDICTIVE VALIDITY AND HETEROGENEITY

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Abstract

Globalization and the development of internet technologies have encouraged the use of information and communications technology (ICT) in higher education institutions, leading to significant change in educational models and teachers' skills. Universities have adapted new technologies and built and maintained their e-learning systems. The most popular learning platforms in higher education are Moodle and Blackboard. Moodle is a free and open access learning platform or course management system. Despite its importance in an educational context, universities are facing problems with limited Moodle usage among teachers and students. The main goal of this experimental study is to analyse students' acceptance of Moodle's web-based resources, such as virtual activities, educational videos and assessment questionnaires, using the technology acceptance model (TAM). A face-to-face survey method was used to collect research data from 303 participants. The questionnaire was composed of five variables and 36 questions. The data was tested using the partial least squares (PLS) method, a form of structural equation modelling (SEM) oriented to the prediction, instead of confirmation, of cause/effect relationships. The analysis of the PLS-SEM corroborated the reliability of the proposed model. The results indicated that the students considered Moodle to be an easy-to-use tool due to sharing similarities with other technological tools. The findings suggest that the Moodle TAM has predictive validity and that heterogeneity should be considered in a higher education institution context. This research applies new PLS developments focused on the benefit of fit, as well as on the predictive performance of the model. The study Moreover, unobserved heterogeneity was accounted for by measuring invariance testing, which is a fundamental requirement for a subsequent comparison of parameters across groups by means of a multigroup analysis offers valuable information for policymakers, researchers and teachers in understanding the composites that influence the implementation of Moodle. The outcomes obtained in this research encourage a variety of lines of investigation focused on the usage of TIC in the classroom.

Keywords: Moodle, Technology Acceptance Model (TAM), Structural Equation Model (SEM), universities.

1 INTRODUCTION

Information and communications technology (ICT) have changed perspectives and behaviours in the world, particularly in the context of education, affecting the design of massification and flexibility strategies through virtual education [1,2]. Most educational institutions have developed virtual learning platforms, making the virtual classroom a learning space for synchronous and asynchronous activities that are critical, collaborative, and reflective to promote the learning process [3]. The virtual classroom complements educational activities and is used fundamentally to manage learning materials and organize the course, including posting notes, videos, tests tutoring schedules, grades, or other information. In general, virtual education does not propose a new teaching approach and maintains the traditional teacher/class one-way communication model. Past research has noted the importance of using virtual classrooms to promote superior academic performance [4], autonomous work [5], teacher–student interaction outside of school hours [6], quality of teaching in the students [7], among others.

Due to the wide acceptance of virtual education, our research purpose is to understand the nature of student acceptance of Moodle's web-based resources, including virtual activities, educational videos, and assessment questionnaires using the technology acceptance model (TAM).

Generally, our findings show that both perceived enjoyment (PEN) and perceived ease-of-use (PEOU) have a positive and direct relationship with the perceived usefulness (PU) of the virtual classroom. Our results also show a positive and direct connection between PU and the attitude towards the usage of a

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virtual classroom, PU and the choice to use a virtual classroom, and the attitude towards using a virtual classroom and the choice to use a virtual classroom.

Our findings contribute to existing TAM literature in several ways. Firstly, this manuscript contributes to previous literature focused on the acceptance of Moodle by finance students at public Spanish universities. Secondly, these findings empirically support the argument that new magisterial course methodologies should feature virtual activities. Thirdly, this article predicts Moodle's use in Spanish universities.

The paper is structured as follows: methodology is explained in the next section, results are discussed in the following section, and finally, the conclusions and implications are presented.

2 METHODOLOGY

The technology acceptance model (TAM), developed by [8], is based on the premise that the acceptance of technology depends on the user's belief about the possible consequences of utilization. Thus, TAM is considered one of the most relevant technology theories in the educational context ([9], [10]). This model is based on the theory of reasoned action (TRA) postulated by [11]. These authors noted that the process of technology acceptance depends on perceived usefulness (PU) and ease-of-use (PEAU), which are two motivational, extrinsic constructs (Figure 1). Thus, TAM models are focused on the technological information, and TRA models are based on the establishment of the attitude, intention, and intensity of final use.

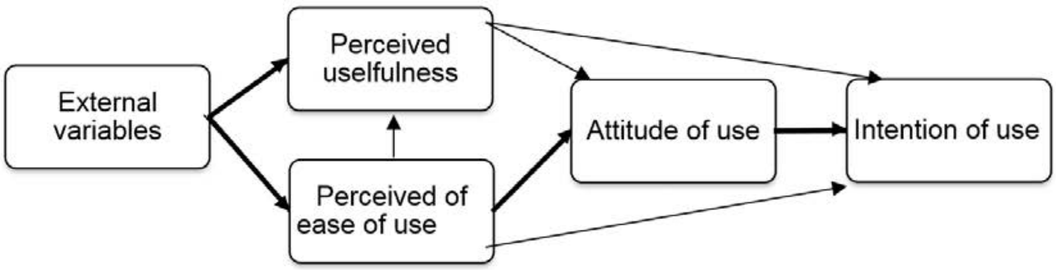

Figure 1. Original Davis's Technology Acceptance Model (TAM)

The core concept of the Technology Acceptance Model (TAM) proposed by [8] is that users' acceptance of emerging information technology will affect users' choices. In our specific TAM model, once users have particular knowledge of emerging information technology through external variables (PEAU and enjoyment of the accumulated experience), they will gain specified perceived usefulness of Moodle. Enjoyment of technology use is related to PU. [12], [13], [14], and [15] show that enjoyment optimizes the user's experience inside the TAM model when perceived usefulness or ease-of-use exists. Consistent with prior studies, we propose the following hypotheses:

Hypothesis 1: *Enjoyment directly and positively influences the virtual classroom's perceived usefulness.*

Hypothesis 2: *Ease-of-use directly and positively influences the virtual classroom's perceived usefulness.*

According to the theory of reasoned action (TRA) ([16], [17]), an individual's attitude plays a significant role in determining their behavioural beliefs towards using the technology and their adoption intention. The models based on TRA ([11]) and TAM ([8]) postulated a positive and significant relationship between attitude towards use, intention to use, and actual use of information systems. [18] and [19] indicated a positive relationship between perceived usefulness and attitude towards virtual classroom use. [20] and [21] provide evidence of a positive and significant relationship between usefulness and intention. [22] showed a direct connection between perceived attitude and intended use of websites. This theoretical TAM basis was evaluated using the following hypotheses:

Hypothesis 3: *Perceived usefulness directly and positively influences the attitude towards virtual classroom usage.*

Hypothesis 4: *Perceived usefulness directly and positively influences the intention to use virtual classrooms.*

Hypothesis 5: *Attitude towards virtual classrooms directly and positively influences the intention to use virtual classrooms.*

2.1 Development of instruments

The data was collected via a face-to-face survey method at a public university located in Spain to collect research data. The questionnaire was separated into different sections to represent each hypothesis. The survey was structured into two steps: 'assessment questions' and 'classification questions.' The assessment questions included five variables: intention, attitude, enjoyment, ease of use, and virtual classrooms' usefulness. On the other hand, classification questions included demographic details such as gender and age. All items were evaluated on a five-point Likert-type scale with anchors from '1 - strongly disagree' to '5 - strongly agree.'

2.2 Sample

The sample used for this study was composed of students from a finance course for the 2018-2019 academic year at a public Spanish university. All of the students were asked to fill out the research questionnaire voluntarily in class. A total of 303 users completed responses to all of the questions. The partial least squares (PLS) estimation technique of structural equation modeling (SEM) was used in this study to predict cause-effect relationships (rather than the confirmation of causality). *Fig. 2* presents the set of latent variables and their relationships specified in a structural equation model that must be examined to test the proposed hypotheses.

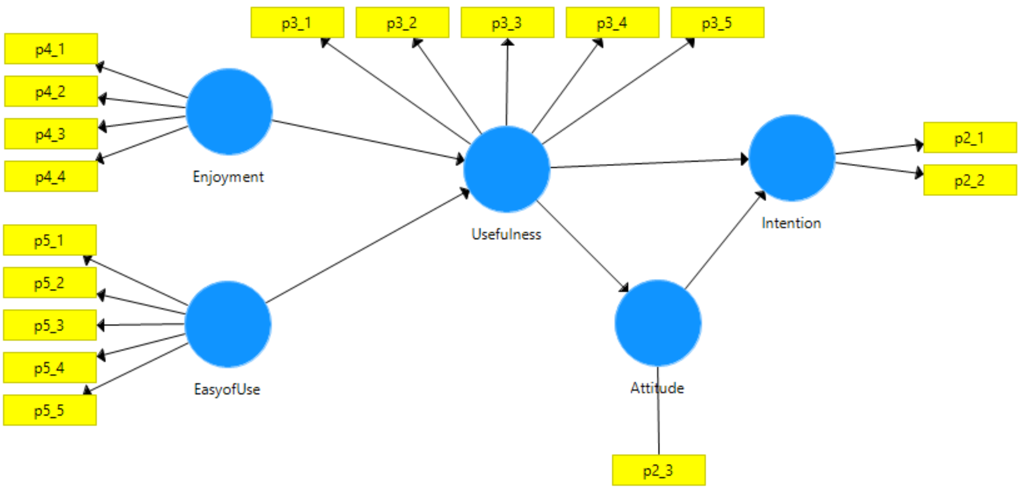

Figure 2. Model to be estimated with SmartPLS.3

2.3 Variables

Table 1 offers a summary of the variables included in the model.

Table 1. Summary of the variables

INTENTION	
P2_1	
P2_2	
ATTITUDE	
P2_3	I have a positive attitude towards using the virtual classroom
USEFULNESS	
P3_1	
P3_2	
P3_3	
P3_4	
P3_5	

ENJOYMENT	
P4_1	
P4_2	
P4_3	Browsing virtual classroom is entertaining
P4_4	Browsing virtual classroom is enjoyable
EASE OF USE	
P5_1	
P5_2	I find it easy to get virtual classroom to do what I want it to do
P5_3	My interaction with virtual classroom is clear and understandable
P5_4	
P5_5	It is easy for me to become skillful at using virtual classroom
P5_6	I find easy to browse the virtual classroom

3 RESULTS

Following [23], this empirical research employs individual item reliability, composite reliability, convergent validity, and discriminant validity to assess the measurement model for reflective constructs. We first evaluated individual reliability (IR) through indicators loading associated with its respective composite, which must be at least 0.707 ([24]). Second, we assessed internal consistency through composite reliability (CR), requiring a measurement of at least 0.6 ([25]). Third, we assessed convergent validity through the average variance extracted (AVE), which must be at least 0.5 ([26]). Finally, we assessed discriminant validity through heterotrait–monotrait (HTMT), which required a value lower than 0.9([27]).

After these assessments, we added test multicollinearity. Multicollinearity refers to linear intercorrelations existing between two or more indicators. High collinearity between these measures would produce unstable estimates since it would be difficult to separate each indicator's distinctive effect on the emerging construct. High levels of collinearity affect the results in two ways: 1) It increases the standard errors and therefore reduces the ability to show that the estimated weights are significantly different from zero; 2) It may result in incorrectly estimated weights and, in extreme cases, changing the signs. To test multicollinearity, the most widely used form of measurement is the so-called variance inflation factor (VIF) ([28]). The authors mention that a VIF> 3.3 indicates collinearity, although a VIF <5 is acceptable ([29]). Table 2 shows the fulfillment of these parameters.

Table 2. Measurement Model by SmartPLS

Composite	Item	IR	CR	AVE	HTMT					VIF
					Attitude	EasyofUse	Enjoyment	Intention	Usefulness	
Attitude	p2_3	1,000	1	1						1,000
Ease of Use	p5_1	0,762								2,078
	p5_2	0,852								2,256
	p5_3	0,563								1,162
	p5_4	0,798								2,065
	p5_5	0,823								2,348
			0,875	0,587	0,409					
Enjoyment	p4_1	0,849								2,050
	p4_2	0,876								3,513
	p4_3	0,875								3,426
	p4_4	0,812								1,799
			0,915	0,728	0,475	0,465				
Intention	p2_1	0,947								2,733
	p2_2	0,948								2,733
			0,946	0,898	0,573	0,467	0,416			

Usefulness	p3_1	0,839							2,292
	p3_2	0,848							2,796
	p3_3	0,866							2,966
	p3_4	0,753							1,553
	p3_5	0,709							1,474
			0,902	0,648	0,579	0,553	0,646	0,574	

We performed a nonparametric bootstrap resampling procedure on 5,000 samples to check the structural model. The hypotheses for the study (Direct effect) were tested using the partial least squares (PLS) structural equations modeling (SEM) technique ([30]). A mediation test (Indirect effect) was also measured by bootstrapping 5,000 resampling analyses with formulated hypotheses ([29], [31]). Estimated path coefficients are statistically significant at 95% when confidence intervals (lower and upper) do not include the value zero ([32]). Table 3 shows fulfilment of all our research hypotheses and mediation tests.

Table 3. Fulfilment hypothesis and mediation test of Structural Model by SmartPLS

Direct effects					
Ho	***Path***	***Beta***	***2.5%***	***97.5%***	***Supported***
H5	Attitude -> Intention	0,378	0,256	0,493	Yes
H2	Ease of Use -> Usefulness	0,286	0,195	0,385	Yes
H1	Enjoyment -> Usefulness	0,454	0,356	0,544	Yes
H3	Usefulness -> Attitude	0,543	0,472	0,613	Yes
H4	Usefulness -> Intention	0,299	0,188	0,416	Yes
Indirect effects					
	Path	***Beta***	***2.5%***	***97.5%***	***Supported***
	Ease of Use -> Attitude	0,155	0,104	0,215	Yes
	Ease of Use -> Intention	0,144	0,092	0,206	Yes
	Enjoyment -> Attitude	0,247	0,184	0,312	Yes
	Enjoyment -> Intention	0,229	0,168	0,294	Yes
	Usefulness -> Intention	0,205	0,136	0,278	Yes

We tested the predicted validity of the structural model with SmartPLS based on three ratios: power (R2), capacity (Q2), and relevance (q2_predict). The coefficient of determination (R2) usually represents a measure of explanatory power in causal models. This ratio indicates the amount of construct variance explained by the predictor variables of the said endogenous construct in the model. The values of R2 range from 0 to 1. In predictive models based on PLS, the meaning is similar. The structural model has more predictive power for each composite if the value is higher. The predictive capacity test (Q2) utilizes a blindfolding procedure, where part of the data for a particular construct is omitted during the parameters estimation, allowing for an estimation of what has been omitted to be determined using the mean and the parameters of the estimated model ([33], [34]). Predictive relevance of PLS models and, more specifically, predictive validity (q2_predict) can be measured using holdout samples. The critical question is whether or not the antecedent variables of an endogenous variable can forecast this dependent variable's behaviour and its indicators in separate samples from the initial data set used to test the theoretical research model. To estimate the value of the indicators of a selected dependent construct, PLS_predict uses the case values of the holdout sample (out-of-sample data) of the independent construct indicators, applying the estimates of the model parameters that were obtained to starting from the sample taken from the total number of observations called 'training sample' to generate predictions of the indicators of the dependent constructs.

We first evaluated predictive power through R2 using a bootstrap resampling procedure. The obtained values in each composite were considered substantial if they were greater than 0.67, moderate if between 0.33 and 0.66, and poor if between 0.19 and 0.32 ([35]). We then assessed predictive capability through Geisser's Stone-Q or Q2 ([33]) using the blindfolding procedure in the cross-validation (redundancy) of each endogenous composite. The obtained values in each composite had to be greater than 0 ([36]). [34] recognizes this ratio can be evaluated in each composite by three levels: Q2 > 0 (low), Q2> 0.25 (medium), Q2> 0.5 (high). Finally, we evaluated predictive relevance through holdout samples of PLS predict (q2_predict) ([37]). The q2_predict ratio can be evaluated in each composite by three levels: small effect is 0.02 ≤ q2 <0.15, moderate is 0.15 ≤ q2 <0.35, and large is q2 ≥ 0.35. Table 4 shows the predictive validity of our model.

Table 4. Predictive validity of the SmartPLS model

Composite	*R2*	*Result_R2*	*Q2*	*Result_Q2*	*q2_predict*	*Result_q2_predict*
Attitude	0,295	Poor	0,288	Medium	0,218	Moderate
Intention	0,355	Moderate	0,313	Medium	0,183	Moderate
Usefulness	0,394	Moderate	0,245	Low	0,383	Large

FIMIX-PLS provides a common approach to deal with unobserved heterogeneity and applies the mixture regression concept to assign observations to groups and estimate group-specific parameters simultaneously ([38]). Moreover, FIMIX-PLS transforms from unobserved into observed heterogeneity to improve out-of-sample predictions. Therefore, FIMIX-PLS algorithms affect prediction relevance, as well as the ex-post analysis to specify observable explanatory composite.

A multigroup analysis is performed to compare significant differences between the two groups obtained by FIMIX (segments). According to [39], it is necessary to study the MICOM (see table 5) before completing the multigroup analysis.

Table 5. Test of invariance of multigroup analysis (MICOM)

Path	*Original correlation*	*Correlation permutation mean*	*5.0%*	*Permutation p-values*	*Mean–permutation difference*	*2.5%*	*97.5%*
Attitude	1,00	1,00	1,00	0,20	-0,01	-0,27	0,25
Ease of Use	1,00	1,00	1,00	0,10	0,00	-0,25	0,26
Enjoyment	1,00	1,00	1,00	0,10	-0,01	-0,26	0,23
Intention	1,00	1,00	1,00	0,90	0,00	-0,26	0,24
Usefulness	1,00	1,00	1,00	0,11	0,00	-0,25	0,25

After the considering measurement invariance, we proceeded to assess whether direct effects of path coefficients between two groups obtained by FIMIX (segments) using the nonparametric method: the permutations test ([39]). The multigroup analysis results (Table 6) indicated that the differences in p-values are not significant except for two paths: Usefulness -> Intention and attitude-> Intention.

Table 6. Multigroup analysis based on FIMIX of SmartPLS model

Path	*Path coefficient segment 1*	*Path coefficient segment 2*	*Difference*	*2.5%*	*97.5%*	*P-value of permutation test*	*Supported*
Attitude -> Intention	0,091	1,000	-0,909	-0,245	0,263		NO
Ease of Use -> Usefulness	0,282	0,129	0,152	-0,224	0,215	0,169	Yes
Enjoyment -> Usefulness	0,439	0,440	-0,001	-0,207	0,209	0,99	Yes
Usefulness -> Attitude	0,418	0,313	0,105	-0,151	0,163	0,191	Yes
Usefulness -> Intention	0,349	-0,001	0,350	-0,261	0,214	0,003	NO

4 CONCLUSIONS

This experimental study’s main goal was to examine student acceptance of Moodle’s using the technology acceptance model (TAM). Based on the results, the acceptance of teaching support technology was examined with models oriented prediction, since they were exploratory models, and we have not performed a confirmatory model research. We found other significant results in our TAM model when we analyzed heterogeneity. FIMIX-PLS implies a two-group solution, with segment one at 72.8% and segment two at 27.2%. According to R2 criteria, the two-group solution fits the data better than an assumption of homogeneity. Therefore, assuming heterogeneity, the model partially improves the explanatory power of R2 statistics for segment two of Attitude (up to 0.43) and Intention (up to 0.99), while usefulness is maintained. Moreover, this is shown in the direct effects of the two path coefficients (see table 6). In part, there is no significant change in the path coefficients of ease of use and enjoyment to usability. However, heterogeneity must be considered, and it is recognized in segment two between two paths: Usefulness -> Intention and Attitude-> Intention.

This finding is relevant for understanding and making predictions based on technological acceptance. There is homogeneity regarding the acceptance of using this technology, but there is heterogeneity when examining Attitude and future Intention. Future behaviour regarding the continued use of the technology was established for only a small portion of users (27.2%).

Several conclusions can be gleaned from this analysis. Our evidence confirms that the TAM's core formulation is valid in the Spanish setting, allowing Spanish researchers to apply findings from previous research to local studies. Additionally, student satisfaction with virtual classrooms is likely to determine whether the student takes subsequent courses that use Moodle as a technological learning tool. Virtual classroom enrichment will influence how teachers, students, and higher education programmes make more efficient and effective courses, and it will be up to researchers in the area to keep up with these advancements. Teachers should make full use of virtual classroom capabilities to improve content quality. If provided with improved course material, students are more likely to use this technological tool to facilitate their learning process and enhance learning effectiveness.

As a final observation, this paper has several limitations. Firstly, there may be unknown composites that could have influenced the variables examined in this investigation. Although we controlled all of the composites identified in past research, theoretical and empirical limitations leave the question of whether or not we examined all relevant composites unclear. Secondly, our study is based on a particular sample and period of time, so our evidence should not be extended to other samples and timeframes. Finally, this document does not consider the opinions and perceptions of virtual classroom professors. When appropriate, our research may lead to further scientific investigation by others in the future. We encourage other academics to extend our analysis to student samples from different academic disciplines to evaluate whether our obtained results still hold true. Inclusion of teachers' perceptions about the use of virtual classrooms as a complementary tool in the magisterial classes would also be interesting.

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