Adoption of Learning Management System Among Students in Higher Educational Institutions - A Case on Moodle LMS

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Abstract. The goal of this research is to investigate the factors that influence students' use of learning management systems (LMSs) in order to facilitate more efficient pedagogy in higher education institutions (HEIs). The data was collected through a structured questionnaire in online form from the students of UG & PG studying in GITAM Deemed to be University, Bengaluru campus. The model was tested by using the following variables perceived usefulness (PU), perceived ease of use (PeU), Attitude (AI)towards using the LMS, Behavior intention (BI) and Actual usage (AU) of LMS. We had tried to extend the TAM by appending the student education (SE), perceived self-efficacy (PsE) and quality of the system (Qos). The findings of the study says that Croanbach's Alpha of all the constructs are above 0.7 and AVE is above 0.5 meeting threshold limits. 7 hypotheses out of 10 are supported. The path coefficients of three relationships PEU» PU, PSE» PU and SE»PEU are not significant. According to the findings of the study, behavior intention is a significant factor in determining actual use of MOODLE. In turn, behavior intention is impacted by both perceived ease of use and perceived usefulness. This study will assist the management, students, teachers, and any other stakeholders in gaining a better understanding of the status of online education.

Keywords: Learning management system Adoption · Technology acceptance model (TAM) · SEM · HEIs · Moodle

1 First Section

1.1 A Subsection Sample

E-learning (EL) is gaining popularity all over the globe as a result of its ability to circumvent the limitations of both time and place inherent in the conventional mode of education. E-learning can be delivered on many different platforms, such as the learning management system (LMS), massive open online courses (MOOCs), and other web-based e-classroom management systems. The Learning Management System is a strong e-learning information system that helps self-learning and delivery. It is an example of the kind of technology that is being used more and more in colleges and universities.

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One of the important web-based developments that can improve e-learning programs is the learning management system (LMS) [1]. Learning management system (LMS) focuses on the delivery of online learning asynchronous and synchronous. In addition to this, it enables the organization of digital educational content, instant messaging, posting, assignments, monitoring the progress of learners, providing blog services, and a lot of other things. [6]. One type of learning management system (LMS) used extensively at universities is Moodle (modular object-oriented term developmental learning environment). As of the year 2021, 350 million users and 42 million courses are taking advantage of this open-source LMS (Moodle 2021). Moodle and G-Learn are the two learning management systems (LMSs) that are most often used at GITAM Universities. Moodle is a user-friendly learning management system (LMS) built on a collaborative e-learning platform, which enables users to share educational content and assignments easily.

Higher educational institutions (HEIs) have adopted EL more due to COVID-19 pandemic. All the HEIs cancelled the classes and send students home, thus enforcing the colleges to provide online classes. EL in universities has skyrocketed since COVID-19. It takes time and effort to arrange and prepare the learning management system, but HEIs that are serious about adopting an e-learning system will reap the benefits [1]. E-learning implementation effectiveness requires institutional support, including financial commitment and recognition of dedication. E-learning systems' long-term success depends on system quality, teachers' and students' self-perceptions, and long-term commitment. [3] suggest that If students don't use e-learning systems regularly, he argues, the systems will fail and yield a poor return on investment (Table 1).

The technological acceptance approach was used to assess Moodle LMS student adoption (TAM). This is the most popular robust theoretical model for LMS uptake at HEIs. The TAM is a robust model with high fit and intention prediction in di-verse situations [2, 4]. In e-commerce, IS used by financial organizations, etc., TAM is frequently used to assess user intent. Academics' inclination to adopt LMS at higher education institutions was determined and predicted by investigating the influence of five external factors, mostly on perceived utility and convenience of use, using the TAM. Many studies have looked at how different people and settings affect the utility and ease of use of a product, perceived self-efficacy (PSE) was used as a personal factor along with PU and PEOU. [22] and Subjective norms (SN), image (I), enabling conditions (FC), and techno-logical complexity (TC) were employed as personal variables, and students [11]. Research uses an integrated structural equation model. Determining the elements actual usage of Moodle LMS in GITAM university. In the next section, we'll talk about the literature review on TAM for LMS applications. Then, we'll talk about the study's goals and the hypotheses that were made. After that, the structural models and measurements that were utilized to test the hypotheses are presented. Finally, study findings, constraints, application possibilities, and future directions are presented.

2 Theoretical Framework & Hypotheses Development

The exogenous aspects (student education, perceived self-efficacy, and quality of system), and the direct impacts among TAM elements (PU, PEOU, BI, & AU) are all

Table 1. Review of existing literature

Authors	Main findings
(Cahir *et al.*, 2014) [7]	The pilot study found that the casualization of the academic workforce was impeding the use of Moodle. Due to the unstable work environment, unit convenors' expertise was observed to be evaporating. Prior to the university-wide rollout, the pilot study was successful in testing Moodle and resolving any technical concerns.
(Sung *et al.*, 2016) [21]	The usage of mobile devices in education had a moderate mean effect size of 0.523, according to a meta-analysis and research synthesis of 110 ex- and quasi-experimental journal papers published between 1993 and 2013. Content analyses of separate studies allowed for a synthesis of the benefits and drawbacks of mobile learning across a range of moderator characteristics with varying effect sizes. The study's results have implications for both theory and practice.
(Jaggars and Xu, 2016) [17]	Grades of students are strongly and positively correlated with the level of interpersonal engagement in a course. Consistent and productive communication between students and teachers fosters a positive learning environment that encourages students to invest in the course and improve their academic performance in it. To investigate the effects of course design elements on student performance, an online course design assessment rubric was created.
(Cole *et al.*, 2014) [10]	In general, students were satisfied with the quality of their online education, and those taking hybrid or partially online courses were even more satisfied. The word "convenience" was mentioned most often as a reason for happiness. "Lack of interaction" was cited most often as a source of dissatisfaction.
(Wong *et al.*, 2019) [23]	The effectiveness of SRL aids in MOOCs and online learning settings is significantly influenced by human variables. For a better understanding of how to assist SRL in MOOCs, further experimental investigations need to be undertaken. Utilizing learning analytics, support may be given to students in the way that suits them the best.
(Wu and Chen, 2017) [20]	This study's overarching goal is to develop a unified model for understanding people's intentions regarding whether or not they will continue to use massive open online courses (MOOCs) by bringing together the technological acceptance model (TAM), the task fit technology (TTF) model, the characteristics of MOOCs, and the concept of social motivation..

(*continued*)

Table 1. (*continued*)

Authors	Main findings
(Masa'Deh *et al.*, 2023) [20]	Positive effects on users' behavior intent were observed for several factors related to information systems, including perceived usefulness, user training, system quality, and management support, but not perceived ease of use.. This was demonstrated through structural equation modelling (SEM). Machine learning (ML) techniques provide high correlation values of up to 80% when predicting behavior intention (BI) from the input components and student loyalty from the factors determining student satisfaction. These high correlation values are indicative of the success of the techniques.. For predicting future targets based on traits independent of input, ML approaches seem promising.
(Sun and Chen, 2016) [20]	It takes well-designed course materials, enthusiastic student-instructor engagement, and well-prepared, well-supported educators to deliver effective online training. It's crucial to establish an online learning community. Technology must improve quickly to provide effective online education.
(Wong *et al.*, 2019) [23]	The effectiveness of SRL aids in MOOCs and online learning settings is significantly influenced by human variables. For a better understanding of how to assist SRL in MOOCs, further experimental investigations need to be undertaken. Utilizing learning analytics, support may be given to students in the way that suits them the best.
(Cole *et al.*, 2014) [10]	This was the case across the board. Students gave their online education an average rating of moderately high quality overall, with hybrid or partially online courses obtaining marginally higher grades than totally online courses on average. The most frequently reported factor for satisfaction was "convenience." The most frequently reported cause of discontent was "lack of interaction."
(Scholtz and Kapeso, 2014) [19]	This research examines mobile learning methodologies for enterprise resource planning (ERP) system training and proposes a theoretical framework for m-learning ERP systems.

ac-counted for in the theoretical model. Below, we evaluate and comment on the formulated hypotheses, represented by the diagram, which reveal the direct effects among the elements. Perceived usefulness (PU) and perceived ease of use (PEOU) of the Moodle LMS appear to be the two most essential beliefs that seem to influence adoption of technology. From the perspective of the theory of reasoned action, TAM concepts are

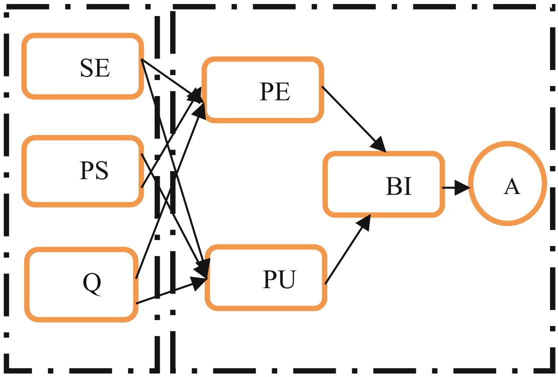

Fig. 1. Theoretical frame of Technology Acceptance Model (TAM), SE – Student education, PSE – Perceived self-efficacy, QoS – Quality of system, PEoU- Perceived ease of use, PU-Perceived usefulness, BI – Behavior intention, and AU- Actual usage of LMS.

derived to better understand people's motives and perspectives when it comes to interacting with and making decisions based on technological and informational systems. Theorems about TAM constructs are as follows:

H_1 BI positively effects the AU of Moodle LMS
H_2 PEOU positively effects BI to use the LMS
H_3 PEOU positively effects PU of LMS
H_4 PSE positively effects PEOU of LMS
H_5 PSE positively effects PU of LMS
H_6 PU positively effects BI to use the LMS
H_7 QOS positively effects PEOU of LMS
H_8 QOS positively effects PU of LMS
H_9 SE positively effects PEOU of LMS
H_{10} SE positively effects PU of LMS

Users of technology, as depicted by the TAM, alter their perspective on the world. Davis (1986) established this paradigm to explain the effects of system characteristics on users of computerized Technology Systems. The TAM is the most often used approach to identifying the factors affecting technological acceptance. The theory states that when given access to novel technology, users' decisions regarding how and when to put it to use are influenced by a number of factors [2]. TAM's goal, as stated by Rondan-Catalua et al. (2015), is to "explain user behavior across a wide spectrum of end-user computing technologies and user groups" by determining what factors contribute to widespread computer adoption. In an effort to identify the primary components that previous research had hinted at, TAM was employed. It describes the relationships between people's opinions, impressions, and plans to use computers [11]. Consumers' timing and methodical approach to adopting new technologies are shown to be sensitive to a number of contextual factors in this model. The two most important factors are "perceived usefulness" (PU) and "perceived ease of use" (PeoU). The two components are defined as follows.

Perceived ease of use is the extent to which a person thinks adopting a certain system would be effortless [11] and Perceived usefulness is the subjective belief of consumers that utilizing specific technology can enhance the quality of their work. According to TAM, the degree to which an information system or technology is embraced by its end users is contingent upon two factors: the perceived usefulness (PU) of the system and the perceived ease of use (PEoU). Together, they shape users' attitudes of the system, which in turn affects their pre-use behavior decisions (Fig. 1).

3 Research Methods

Identical to the earlier studies, this research paper used a quantitative method as the foundation for its research methodology. A random sample of 150 students from the current academic year in GITAM University, Bengaluru campus were collected using google forms, the research was conducted during October 2022 to December 2022. The students were initially made aware of the questionnaire's anonymity and the fact that the date is collected only be used for the research. Students who utilized Moodle LMS were asked to participate in the survey, giving them the option to decline if they chose.

The survey consisted of 25 items: "SE" three items, "PSE" four items, "QOS" three items, "PEOU" four items, "PU" five items, "BI" three items and "AU" three items. Responses were captured using a seven-point Linkert scale "1-strongly disagree to 7-strongly agree". We adopted all the items from the earlier studies which used TAM model but not specifically in Moodle learning management system. The adopted questionnaire was based on the earlier studies.

Methods of statistics that were used: The method of Partial Least Square-Structural Equation Modelling (PLS-SEM), which is also known as Variance-Based Structural Equation Modelling, is the strategy that is utilized for the goal of conducting analysis. The analysis was conducted using the model described above [15]. This analysis uses a modern multivariate model to examine the correlations between many sets of variables [13]. Because it is adaptable to different sample sizes and different normal distributions, this methodology is excellent for use in confirmatory analyses. PLS-SMART was the software that was used to carry out the investigation.

4 Data Analysis

PLS-SEM, which stands for partial least square structural equation modeling, was used so that the conceptual model could be investigated. As a result of the characteristics of the study and the absence of normalcy in the distribution of the samples [12] In comparison to covariance-based (CB) SEM, PLS-SEM was deemed more applicable. Secondly, when comparing PLS-SEM with PROCESS for evaluating mediation analysis, the latter is currently recommended because of its superiority [13]. Finally, PLS-SEM outperforms CB-SEM statistically [13]. This analysis relied on SmartPLS 4, which was developed by the authors. The model was tested using a two-pronged analytical technique developed by Anderson and Gerbing (1988) (Hair *et al.*, 2019) [18]. The measurement model's validity and reliability were first tested with the PLS algorithm, and then the hypotheses and controls were tested with the bootstrapping method.

4.1 Measurement Model

In PLS-SEM, we may calculate the robustness, convergent validity, and discriminant validity of a reflective measurement model [9]. SmartPLS provides two measures, Cronbach's a and rho A (r A), to assess the constructs' internal consistency (reliabil-ity) [13]. The convergent validity is judged based on three criteria: The outer/factor loadings of all items must be greater than 0.5 [5] or 0.7 [12]. The average extracted variance (AVE) for each construct should be more than 0.5 [13]. According to [13], The overall construct dependability must be greater than 0.7. For this investigation, every criterion has been satisfied. Check out the first table. Checking the discriminant validity If there is a clear distinction between all constructions [24]. [14] Given the inefficiency of the Fornell-Larcker criterion and cross-loadings in detecting problems with discriminant validity, he advocated for the adoption of the heterotrait-monotrait (HTMT) ratio as a criterion for PLS-SEM. Those who err on the side of caution should aim for an HTMT ratio of less than 0.85, however a value of less than 0.90 may also be considered appropriate [13, 14]. All constructs pass the HTMT test for discriminant validity. Results for discriminant validity can be seen in Table 2.

4.2 Assessment of Structural Model

After the validity and reliability of the measurement model assessment are verified, the structural model evaluation can begin. To investigate the magnitude of latent variables' direct and indirect effects on the dependent variable, we conducted a structural model analysis. Additionally, t-values, the significance of path coefficients, and indirect correlations between components were analyzed using the bootstrapping approach, which included 10,000 bootstrap sub-samples. The approximation model fit was then evaluated using the standardized root mean square residual (SRMR) [8]. The approximation model fit was then evaluated using the standardized root mean square residual (SRMR) [15, 16]. Ideally, the SRMR value would be lower than 0.08. An SRMR of 0.078 was found to exist in the present investigation (Table 4 and Fig. 2).

As it is shown in the Table 3, 7 among 10 hypotheses are supported. The extent and importance of links between various constructs are indicated by the path coefficients. The structural model discloses positive relationship between Behavioral intention (BI) towards Actual use of MOODLE LMS (AUM) ($\beta = 0.620$, $t = 10.488$, $p = 0.000$), Perceived ease of use (PEU) positively influences Behavior intention ($\beta = 0.334$, $t = 4.212$, $p = 0.000$). Not enough evidence exists to support hypothesis 3, which proposes that a positive correlation between perceived ease of use and PU exists ($p = 0.144$). A high level of PSE is associated with a favorable opinion of the product's use (=0.646, $t = 10.299$, $p = 0.000$). The results for H5 (self-efficacy in regards to perceived usefulness) are not significant ($p = 0.066$). The results for Hypothesis 6 (Perceived Usefulness in Influencing Behavior Intention) are in agreement with the null (=0.518, $t = 7.096$, $p = 0.000$). We find that H7, Quality of system (QOS) as it relates to user friendliness, is true (=0.163, $t = 2.204$, $p = 0.028$). Perceived usefulness is affected by the quality of the system (=0.403, $t = 4.456$, $p = 0.000$), lending credence to hypothesis 8. There is no statistically significant correlation between student education (SE) and perceived ease of use ($p = 0.481$). Student education has a significant positive influence on Perceived usefulness, as predicted by hypothesis 10 (=0.292, $t = 3.104$, $p = 0.002$).

Table 2. Measurement model indicators

Construct	Code	Item	Outer loading	α	ρA	AVE
Student Education	SE1	I am a self-directed person when it comes to learning and studying.	0.958	0.937	0.940	0.888
	SE2	I am driven and focused in my academic pursuits.	0.942			
	SE3	Effective time management has allowed me to meet all of my academic and work deadlines.	0.926			
Perceived self-efficacy	PSE1	If I had access to the LMS instructions, I would be able to complete the assignment utilizing the LMS.	0.877	0.809	0.809	0.637
	PSE2	I could use the LMS if I could obtain help if I got stuck.	0.851			
	PSE3	Moodle has assisted me in achieving the module's learning objectives.	0.892			
	PSE4	Moodle facilitates communication with the lecturer and other students.	0.743			
Quality of system	QOS1	Moodle's response speed is acceptable.	0.944	0.859	0.867	0.876
	QOS2	Moodle offers extensive availability.	0.946			

(*continued*)

Table 2. (*continued*)

Construct	Code	Item	Outer loading	α	ρA	AVE
	QOS3	Moodle provides appealing features to entice users.	0.890			
Perceived ease of use	PEU1	It would be simple for me to acquire LMS expertise.	0.901	0.932	0.932	0.831
	PEU2	My interactions with LMS would be transparent and straightforward.	0.925			
	PEU3	The LMS would be simple to use.	0.920			
	PEU4	It would be simple for me to get LMS to perform the actions I desire.	0.900			
Perceived usefulness	PU1	LMS might be useful for my job.	0.838	0.855	0.881	0.646
	PU2	Using LMS would increase my efficiency at work.	0.810			
	PU3	Using LMS at work would boost my efficiency.	0.893			
	PU4	Utilizing an LMS would enhance my job performance.	0.546			
	PU5	Overall, I am satisfied with my Moodle experience.	0.882			
Behaviour intention	BI1	I hope to utilise LMS's features and content in the future.	0.948	0.937	0.937	0.887
	BI2	I plan on making good use of LMS's tools and materials to supplement my education.	0.926			
	BI3	I aim to utilise LMS's features and content as frequently as feasible.	0.952			

(*continued*)

Table 2. (*continued*)

Construct	Code	Item	Outer loading	α	ρA	AVE
Actual use of MOODLE LMS	AUM1	I like utilising Moodle for my academic work.	0.837	0.742	0.748	0.794
	AUM2	LMS is highly desirable for academic and associated reasons, in my opinion.	0.878			
	AUM3	I have a generally positive opinion toward LMS usage.	0.852			

Table 3. HTMT ratio Discriminant validity

	AU	BI	PEoU	PSE	PU	QoS
BI	0.73					
PEoU	0.8	0.7				
PSE	0.84	0.79	0.88			
PU	0.76	0.8	0.69	0.86		
QoS	0.51	0.67	0.59	0.82	0.83	
SE	0.46	0.57	0.51	0.68	0.76	0.68

Table 4. Structural model path coefficients

Hypothesis		Direct path coefficient	T-stat	p-value	Results
H1	BI» AUM	0.620	10.488	0.000	Supported
H2	PEU» BI	0.334	4.212	0.000	Supported
H3	PEU» PU	0.120	1.462	**0.144**	Not supported
H4	PSE»PEU	0.646	10.299	0.000	Supported
H5	PSE» PU	0.175	1.842	**0.066**	Not supported
H6	PU» BI	0.518	7.096	0.000	Supported
H7	QOS» PEU	0.163	2.204	0.028	Supported
H8	QOS» PU	0.403	4.456	0.000	Supported
H9	SE» PEU	0.066	0.705	**0.481**	Not supported
H10	SE» PU	0.292	3.104	0.002	Supported

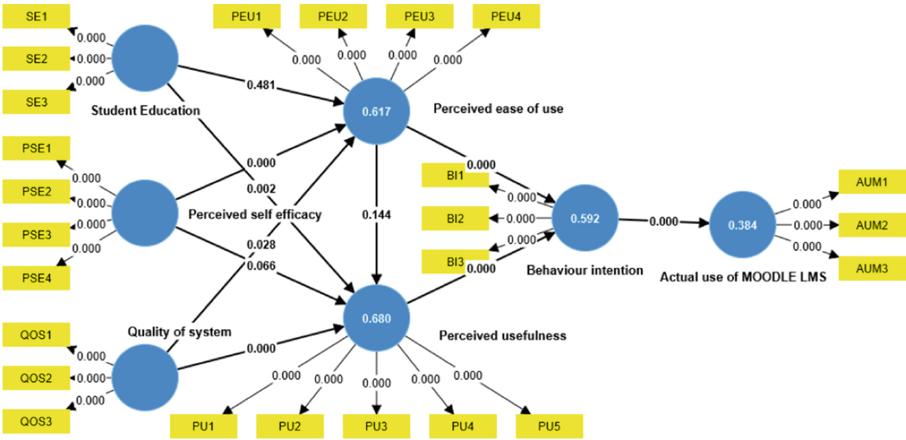

Fig. 2. Structural model

5 Discussion and Conclusion

The purpose of this study was to investigate the impact of various factors on the actual use of MOODLE Learning Management System. In addition to this, the current study is important because it investigates the various elements that have an influence on the actual use of MOODLE through behavior intention. Student education perceived self-efficacy, quality of system, perceived ease of use, perceived utility, behavior intention, and actual use of MOODLE learning management system are the seven constructs that make up the structural model in this study.

According to the findings of this study, behavioral intention has a positive influence on the actual use of MOODLE LMS, and behavioral intention is positively influenced by both perceived ease of use and perceived usefulness. Additionally, behavior-al intention is positively influenced by perceived usefulness. The perceived self-efficacy of the user and the quality of the system both have a favorable impact on the perceived ease of use, however the education level of the user does not have any bearing on this perception. Only positive influences, such as student education and the quality of the system, can be attributed to perceived utility. It does not have any influence from Perceived self-efficacy, and it does not have any influence from Perceived ease of use either. Neither factor has any effect on Perceived usefulness.

In conclusion, the findings of the study indicate that actual use of MOODLE is driven by users' behavior intentions, and that behavior intentions are influenced by both users' perceptions of how easy MOODLE is to use and how beneficial it is. Because perceived usefulness is not affected in any way by perceived ease of use, this demonstrates that the two constructs, perceived usefulness and perceived ease of use, each have their own unique significant impact on behavior intention.

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