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Exploring Students' Acceptance Level of Learning Management System (LMS) as E-learning Platform using Technology Acceptance Model (TAM) at Manado State University

Keith Francis Ratumbuisang[1*], *Yosua Fitsgerald Ratumbuisang*[2], Djubir Ruslan Eddy Kembuan[3], Johan Reimon Batmetan[4], Merriam Modeong[5]

[1,4,5]Universitas Negeri Manado, ICT Education Department, Tondano, Indonesia
[2]Universitas Negeri Yogyakarta, Technical and Vocational Education Department, Yogyakarta, Indonesia
[3]Universitas Negeri Manado, Architecture Department, Tondano, Indonesia

Abstract. This study aims to identify elements that can project the use of e-learning among Manado State University students through the application of path analysis. This study utilizes the Technology Acceptance Model (TAM) framework as a theoretical foundation that guides in analysing the relationship between external and internal variables. The series of concepts proposed involves six main variables, as shown in Figure 1. The model presents the concept of supporting condition variables as an integrated external element in the Technology Acceptance Model. According to the analysis, AT, BI, FC, PEU ATU impact the desire to utilize LMS, When the endogenous latent variable's Q-square score is positive, indicating that the endogenous latent variable is predictive. Meanwhile, hypothesis testing revealed that one of the eight submitted hypotheses, H4, was rejected, while the others were approved.

* Corresponding author: keithratumbuisang@unima.ac.id

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1 Introduction

Advances in information technology have resulted in the emergence of new applications in the realm of education [1]. E-learning is a form of education that uses computer technology to provide learning materials to students, because of this development [2]. The Learning Management System (LMS) platform remains the most widely used means of implementing online learning in most higher education institutions [3]. A flexible system that allows institutions to distribute learning materials to many students anywhere and at any time is known as an e-learning system [4]. The Learning Management System is a form of learning media integration that uses an integrated platform to manage communication procedures in all educational activities [5]. Online cooperative learning using innovative technological platforms like Edmodo, social media, Blogs, Coursera, or custom platforms created by educational institutions, has revolutionized the educational methodology previously overseen solely by computers. According to study by [6][7], students are projected to achieve significant academic progress because of the growing popularity of digital learning. The availability of favorable facilities that enhance the overall learning experience and the cost-efficiency element are the two main drivers driving the inclusion of online learning in colleges.

[8]The Learning Management System is not only the foundation for distance education but is also often used to strengthen the traditional teaching process in higher education through what is known as a blended learning approach [9]. Numerous benefits can be gained by students, educators, and academic staff through the utilization of an LMS. For instance, they can revisit lecture materials, offer assessments, engage in examinations and assignments, initiate discourse, and socially interact (reference [10]). Furthermore, the Learning Management System also empowers students to make use of interactive functionalities like threaded conversations, video conferences, and discussion platforms (source [11]). The research methodology applied in this study pertains to a constructional approach rooted in the Technology Acceptance Model (reference [12]). The array of proposed concepts encompasses six primary variables, as illustrated in Figure 1. The model introduces the notion of supportive condition variables as an integrated external element within the Technology Acceptance Model.

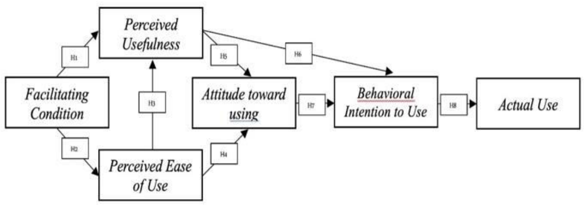

Figure 1.
Technology Accpeted Model (TAM) Framework

2 Method

The research model depicted in Figure 1 is an An adjusted version of the Technology Acceptance Model (TAM) was utilized in this study, incorporating six primary components: Facilitating Conditions, Perceived Usefulness, Perceived Ease of Use, Attitude towards Usage, Behavioral Intention to Use, and Actual Use. Data was gathered from 121 participants through a specially crafted survey. The collected information was then processed using SmartPLS software and subjected to analysis through the Structural Equation Modeling-Partial Least Squares (SEM-PLS) approach.

In the context of Partial Least Squares Structural Equation Modeling (PLS-SEM), the testing process involves two primary phases: initially evaluating the outer model, followed by scrutinizing the inner model. The purpose of examining the outer model is to verify the credibility and consistency of the data employed in the research. This validation procedure encompasses two critical evaluations: confirming the convergent validity and establishing the discriminant validity. Convergent validity is assessed using two key indicators: the Average Variance Extracted (AVE) metric and the loading value of the outer model. It is anticipated that the AVE value should exceed 0.5 [13]. Failure to meet this criterion for any AVE value necessitates the removal of the associated latent variable from the model. In the context of assessing convergent validity through outer loading, a value higher than 0.7 is anticipated for confirmatory research, whereas a value higher than 0.5 (or within the range of 0.5 to 0.6) is considered appropriate for exploratory research [14]. Any outer loading value below 0.4 requires the exclusion of the corresponding loading from the model [13].

3 The assessment of discriminant validity included either cross-loading or a contrast between the square roots of AVE and the correlations among latent variables. In this examination, the square root value of AVE must exceed the correlation value among latent variables to confirm reliable Discriminant Validity. To ensure the reliability of the data, Cronbach's alpha value was computed, with a minimum acceptable level of 0.7. Indicators or variables that didn't meet this requirement during the outer model assessment would be eliminated, and iterative adjustments would be performed until all the remaining indicators and variables fulfilled the prescribed requirements.

When all variables and indicators fulfilled the minimal test criteria, the attention turned to the evaluation of the inner model, which aimed to uncover relationships between latent variables. This evaluation encompassed three primary components: R-Square testing, Q-Square testing, and hypothesis testing. R-Square values were categorized as substantial, moderate, or weak. An R-Square value exceeding 0.67 was classified as strong, while values of 0.33 and 0.19 fell into the medium and weak categories, respectively [12]. A positive Q-Square value indicated the model's predictive relevance, while a negative value indicated the opposite.

Hypothesis testing served to elucidate the degree of influence and relationship among latent variables. The Original Sample value indicated the direction of the latent variable's relationship—positive if the value was greater than zero and negative if it was less than zero. The proposed hypotheses aligned with the TAM framework in the following manner:

H1: Facilitating Conditions are expected to positively impact the perception of usefulness.
H2: Facilitating Conditions are predicted to positively influence the perception of ease of use.
H3: The perception of ease of use is anticipated to have a favourable impact on the perception of usefulness.
H4: The perception of ease of use is expected to positively affect the attitude towards using.
H5: It is postulated that the perception of usefulness positively contributes to the attitude towards using.
H6: It is suggested that the perception of usefulness positively contributes to the intention to use.
H7: The attitude towards using is hypothesized to positively influence the intention to use.
H8: The intention to use is hypothesized to have a positive effect on the actual usage behavior.

An hypothesis becomes accepted when its P-Value is below 0.05. A connection is considered noteworthy if the resultant value is equal to or greater than the T-Table value (T-Statistic $\geq$ 1.96). Conversely, the connection is deemed inconsequential if the resulting T-Statistic value falls below the T-Table value [13]. By evaluating the conducted data testing, a determination can be made regarding the acceptance or rejection of the proposed hypothesis.

4 Result and Discussion

Respondents collected for this study were 121 respondents. Demographic analysis in this study includes several demographic groups, namely gender, and the origin of the faculty.

Table 1. Respondent Demographic Analysis

No		Informasi	Total
1.	Gender	Male	45
		Female	76
2.	Faculty	Engineering	18
		Economics and Business	17
		Social and Law	18
		Educational Science and Psychology	18
		Mathematics and Natural Sciences	17
		Sports Science and Public Health	16
		Language and Art	16
Total			121

After collecting the data, it goes through a sequence of analyses in the phase of testing the outer model. In this stage, the precision and uniformity of the gathered data are examined. Determining the precision of the data involves two separate techniques: one pertains to the consistency of results and the other relates to the distinctiveness of outcomes. The evaluation of data precision through consistency includes two methods: an assessment grounded on values of external loading, and an investigation using the Average Variance Extracted (AVE). The findings from scrutinizing the external loading values are elaborated in Table 2, whereas the outcomes from the evaluation using AVE can be seen in Table 3.

Table 2. Convergent validity test results using outer loading.

Indicator	Outer Loading	Description
AT1	0.821	accepted
AT2	0.881	accepted
AT3	0.872	accepted
AU1	0.999	accepted
AU2	-0.017	rejected
BI1	0.893	accepted
BI2	0.889	accepted
FC1	0.848	accepted
FC2	0.889	accepted
FC3	0.872	accepted
PEU1	0.707	accepted
PEU2	0.810	accepted
PEU3	0.817	accepted
PEU4	0.820	accepted
PU1	0.817	accepted
PU2	0.831	accepted
PU3	0.771	accepted

Referring to Table 2, most indicators exhibit outer loading values exceeding 0.5. However, there is a single indicator with a value below 0.5, specifically the AU2 indicator with a value of -0.017. As a result of this analysis, one indicator will be eliminated, necessitating a recalculation.

Table 3. Convergent validity test results with AVE

Indicator	AVE	Description
AT	0.499	Rejected
AU	0.736	Accepted
BI	0.794	Accepted

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FC	0.710	Accepted
PEU	0.624	Accepted
PU	0.651	Accepted

Table 3 shows that almost all underlying variables have an Average Variance Extracted (AVE) of more than 0.5. Among these variables, AT has the lowest AVE value, just below 0.5 at 0.499, whereas BI has the highest AVE value at 0.794. To assess the validity of the data using discriminant validity, an analysis of cross-loading values was performed. The results of this cross-loading test are outlined in Table 4.

Table 4. Test results with cross loading

	AT	AU	B	FC	PEU	PU
AT						
AU	**3.448***					
BI	3.360	**1.094***				
FC	3.181	0,6375	**1.230***			
PEU	3.000	1.055	1.088	**1.171***		
PU	3.258	1.025	1.133	1.087	**1.183***	

In Table 4, the average variance extracted (AVE) square root value exceeds the relationship between latent variables. This demonstrates that all latent variables received good Discriminant Validity evaluations and met the Discriminant Validity requirements. Cronbach's alpha and the composite reliability values were also evaluated as part of the reliability assessment. Tables 5 and 6 provide specifics on the Cronbach's alpha value and composite reliability rating.

Table 5. Cronbach's alpha Score

Indicator	*Cronbach's Alpha*	Description
AT	0.096	rejected
AU	0.839	accepted
BI	0.741	accepted
FC	0.786	accepted
PEU	0.792	accepted
PU	0.735	accepted

According to the computations, as displayed in Table 5, the Alpha Cronbach score for nearly all essential variables inside the structure are greater than 0.7. The latent variable AT displays the least Cronbach's Alpha score at 0.491, whereas the latent variable AU displays the greatest Cronbach's Alpha at a value of 0.893.

Table 6. Composite Reliability Score

Indikator	*Composite Reliability*	Description
AT	0.491	rejected
AU	0.893	accepted
BI	0.885	accepted
FC	0.880	accepted
PEU	0.869	accepted
PU	0.848	accepted

Based on the findings in Table 6, the composite reliability values of most latent variables are above 0.7. The latent variable AT demonstrates the lowest value at 0.491, while the highest value is observed in the latent variable AU at 0.893.

Once all variables and indicators meet the required criteria, the subsequent phase involves evaluating the inner model. The outcomes of the inner model analysis indicate three essential tasks: R-Square assessment, Q-Square assessment, and hypothesis testing encompassing P-Value examination, T-Statistics, and scrutiny of the Original Sample. The results for R-Square are displayed in table 7, while those for Q-Square can be found in table 8. Details of the hypothesis testing outcomes are available in table 9.

Table 7. R-Square

	R-Square	Description
AU	0.610	Moderate
ATU	0.732	Strong
BI	0.799	Strong
PEU	0.650	Moderate
PU	0.858	Strong

According to an analysis of the R-Square results shown in Table 7, the PU variable exhibits the highest R-Square value, which is 0.858. This numerical illustration shows that the FC and PEU variables have a strong influence on the BI hidden variable. The AU latent variable, on the other hand, has an R-Square value of 0.610, indicating that the BI latent variable shapes the impact on the AT latent variable. An observed value of 0.732 for the ATU latent variable indicates that the PU and PEU latent variables are the main driving forces for the ATU latent variable. An R-Square value of 0.799 is recorded for the latent variable B, showing that the influences.

Table 8. Q-Square

	Q-Square	Description
AU	0.475	predictive
ATU	0.558	predictive
BI	0.623	predictive
PEU	0.640	predictive
PU	0.691	predictive

Information presented in Table 8 reveals that each of the The internal hidden variables show promising Q-square results. Particularly, the PU hidden variable has the highest Q-square score at 0.691. Following that, the PEU hidden variable exhibits a Q-square value of 0.640, while the latent variable B has a value of 0.623. Similarly, the ATU hidden variable records a Q-square score of 0.558, whereas the AU latent variable indicates the lowest value at 0.475. Together, these results emphasize the importance of all internal latent variables in the model suggested by this study for making predictions.

Table 9. Results of Hypothesis testing

Hipotesis	*Original Sample*	*T-Statistic*	*P-Value*	*Description*
H1: FC -> PU	0.301	5.141	0.000	accepted
H2: FC -> PEU	0.806	22.671	0.000	accepted
H3: PEU -> PU	0.666	13.027	0.000	accepted
H4: PEU -> ATU	0.713	4.811	0.351	rejected
H5: PU -> ATU	0.154	0.936	0.000	accepted
H6: PU – BI	0.445	6.516	0.000	accepted
H7: ATU -> BI	0.497	6.445	0.000	accepted
H8: BI - AU	0.781	19.280	0.000	accepted

The information presented in Table 9 demonstrates that H1, H2, H3, H5, H6, H7, and H8 display a positive initial sample value. The t-statistic goes beyond 1.96, while the p-value is lower than 0.05. This result indicates that the hypothesis is accepted, indicating a meaningful and significant influence of external factors on internal variables. On the other hand, the hypothesis represented by H4 is rejected due to a p-value that exceeds 0.05. This outcome implies an adverse and negligible effect of external variables on the internal variables within the connection.

The study involves the testing of both convergent validity and discriminant validity. Convergent validity is evaluated by using two methods: the outer loading value and the Average Variance Extracted (AVE). Most of the indicators listed in Table 2 demonstrate outer loading values that are higher than 0.5, indicating their significant contributions to the measured variable. However, there is a noteworthy exception observed in the case of the AU2 indicator, which displays an outer loading value of below 0.5 at -0.017. This result implies that the influence of AU2 on the measured variable is limited, and its connection might diverge from the expected hypothesis or research objectives.

The analysis findings are presented in Table 3, showcasing AVE values for various latent variables. Virtually all latent variables record AVE values surpassing 0.5, implying robust recovery rates for most of them. Elevated AVE values signal that the latent variable effectively captures variation among indicators. Among these variables, latent variable AT holds the lowest AVE value of 0.499, indicating a slightly weaker recovery rate compared to other latent variables. AVE values approaching or falling below 0.5 could indicate inadequate representation of indicator variation. On the other end, the BI latent variable boasts the highest AVE value of 0.794, pointing to an exceptionally strong recovery rate. Elevated AVE values again indicate proficient representation of indicator variation.

In general, latent variables included in the confirmatory factor analysis display impressive levels of recovery. However, there are noticeable differences in the recovery rates among these latent variables. The accuracy of the data's validity, assessed through discriminant validity, was examined by analyzing cross-loading values. The results from Table 4 illustrate that the square root of AVE (Average Variance Extracted) for each latent variable exceeds the correlation value between them. This indicates that all latent variables meet the criteria for discriminant validity and possess strong distinguishing attributes. Essentially, all latent variables investigated in this study exhibit favorable traits for differentiation, as evidenced by the square root of AVE surpassing the correlation value between the latent variables.

Assessment of data reliability was executed by evaluating both Cronbach's alpha and composite reliability values. Cronbach's Alpha value for the majority of latent variables in the model exceeds 0.7. This indicates that the latent variables in the model display a reasonably high level of reliability, given the generally accepted threshold of 0.7. This implies that the measurement instruments employed in the model demonstrate a satisfactory degree of consistency. Notably, the latent variable AT exhibits the lowest Cronbach's Alpha value of 0.491, whereas the latent variable AU boasts the highest value of 0.893. This discrepancy signifies that the latent variable AT may possess lower reliability compared to the other latent variables in the model, whereas the AU latent variable demonstrates higher reliability. Consequently, the measurement instruments employed in the model collectively showcase respectable reliability, despite the relatively lower reliability of the AT latent variable. Almost all latent variables manifest a Composite Reliability value surpassing 0.7, a generally acknowledged threshold for satisfactory reliability. However, an exception emerges with the latent variable AT, which holds a Composite Reliability value of 0.491, indicating diminished reliability in comparison to the other variables. Conversely, the latent variable AU stands out with the highest Composite Reliability value of 0.893, signifying heightened reliability in capturing relevant concepts. In summary, most latent variables exhibit a commendable level of reliability, yet special consideration should be directed towards the AT latent variable due to its lower reliability. Additionally, the latent variable AU demonstrates robust reliability in assessing associated concepts.

Once all variables and indicators meet the required test criteria, the subsequent phase involves examining the inner model. This stage comprises three essential tasks: conducting R-Square and Q-Square tests, as well as hypothesis testing encompassing P-Value, T-Statistics, and the Original Sample. Among these, the PU variable exhibits the highest R-Square value of 0.858, indicating a significant influence of the PU variable (Perceived Usefulness) and the FC variable (Facilitating Conditions) on the BI latent variable (Behavioral Intention). Similarly, the AU variable holds an R-Square value of 0.610, signifying the influence of the BI latent variable on the AT

(Attitude towards Technology) latent variable. Additionally, the ATU variable demonstrates an R-Square value of 0.732, revealing the impact of the PU and PEU (Perceived Ease of Use) latent variables on the ATU (Actual Technology Usage) latent variable. Moreover, the BI variable's R-Square value is 0.799, underscoring the influence of the latent variables ATU and PU on the latent variable B (behavior intention). Meanwhile, the PEU variable showcases an R-Square value of 0.650, denoting its connection with the FC variable.

All latent variables within the research model hold noteworthy predictive relevance, with PU exhibiting the highest predictive relevance, trailed by PEU, BI, ATU, and AU. In terms of original sample values, Variables H1, H2, H3, H5, H6, H7, and H8 demonstrate positive values, signifying that their average values exceed zero. The corresponding t-statistic values surpass 1.96, suggesting that the differences between the sample mean and zero are statistically significant. Additionally, the P-values for these variables are less than 0.05, indicating robust evidence in favor of the proposed hypothesis – namely, the positive and substantial influence of exogenous variables on endogenous variables.

However, the H4 hypothesis is rejected due to its p-value exceeding 0.05. This outcome suggests a negative and insignificant relationship between exogenous and endogenous variables. Overall, the statistical analysis outcomes demonstrate that H1, H2, H3, H5, H6, H7, and H8 variables positively and significantly affect endogenous variables. On the contrary, the H4 variable fails to exhibit a substantial effect on endogenous variables.

The purpose of this study was to pinpoint the factors that affect users' decisions to utilize LMS as an e-learning platform. The intention to adopt LMS was therefore evaluated using the TAM model. For analyzing respondent data, the study used the partial least squares structural equation modeling (PLS-SEM) technique. The results of the calculations show that the influence of AT, BI, FC, PEU, and ATU on the intention to utilize LMS. Additionally, the endogenous latent variables' Q-square values are positive, demonstrating their predictive utility. In terms of hypothesis testing, H4, one of the eight proposed hypotheses, was disproved. Seven other hypotheses—H1, H2, H3, H5, H6, H7, and H8—were, on the other hand, approved.

5 Conclusion

The main goal of this study was to investigate the factors that influence users' adoption of a Learning Management System (LMS) when used as an E-Learning platform. To achieve this aim, the researchers employed the Technology Acceptance Model (TAM) to assess users' intention to make use of the LMS. Additionally, they utilized the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique to analyze the data collected from participants. The outcomes of the computations demonstrated that several factors, including Actual Usefulness (AT), Perceived Ease of Use (PEU), Behavioral Intention (BI), Facilitating Conditions (FC), and Actual Use (ATU), have an impact on users' willingness to engage with e-health services. Furthermore, the analysis revealed a positively significant Q-square value for the endogenous latent variable, indicating its strong predictive significance. Concerning the hypotheses testing, the results showed that out of the eight hypotheses proposed, one hypothesis (H4) was not supported, while the other seven hypotheses (H1, H2, H3, H5, H6, H7, and H8) were supported by the research findings.

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