

Computer Self-efficacy on Using Learning Management System: From the Lens of Undergraduate Students

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Abstract—The development of technological shapes to support learning process both online and offline becoming more diverse to achieve the learning quality with ease, flexible and effective. Learning Management Systems (LMS) are examples of Internet-based technology that are commonly employed in developed countries. However, the number university using LMS as media learning support in developing countries such as Indonesia are limited. Many factors both support and hinder the practical usage of LMS. As a result, the goal of the study was to assess the factors influencing the successful usage of LMS at the university using the Delone McLean model approach (D&M). This model was modified, and a broad factor called Computer Self-Efficacy (CSE) was introduced, which was tested using a questionnaire on 311 undergraduate students. Six hypotheses were tested, four of which were supported and two were rejected. Based on these findings, it concluded that this study had helped to modify the D&M model, which can improve the ability of students' services in online learning and encourage students' self-efficacy gradually.

Keywords—Delone Mclean model, computer self-efficacy, learning management system

I. INTRODUCTION

Internet technology has significant influenced to the quality of digital learning process in the classroom. Teachers and students are affected by online university learning [1]. Additionally, growing in popularity is technology-based education in emerging nations, notably in Southeast Asia.

Both internal and external causes influence technology development. LMS-based learning technology is common in developing nations [2]. Most of the users of LMS are university students and teachers. It will become clear from examining the implementation that user satisfaction shows how well the technology was implemented. As a result, the model theory method must serve as the foundation for evaluating this achievement.

Self-efficacy is a user trait that is a fascinating example of how everyone has different views. In order to improve job performance, a person must have self-efficacy, which is the belief in one's capacity to fulfill tasks [3]. Although self-efficacy is commonly utilized in various user technology issues, according to prior research, only some have used it to assess how well LMS technology has been implemented.

This study aims to identify the elements that affect university students' satisfaction with the LMS. In order to determine if a user has confidence using the LMS, which affects the chance that performance will increase, the researchers apply the Delone McLean (D&M) model theory method and add the computer self-efficacy (CSE) element.

Numerous LMS acceptance studies [4, 5] have used the Technology Acceptance Model (TAM) model and the Unified Technology Acceptance and Use of Technology (UTAUT) model. According to Jeyaraj [4], technology users' behavioral attitudes are measured using internal and external elements using the TAM and UTAUT models. Due to user behavior limitations, TAM and UTAUT models are unable to assess technology usage.

Because a similar model has been widely used in earlier research, the Information System (IS), which uses the system and satisfaction [4], is usually used in the theory of D&M model. The most popular TAM and UTAUT models were employed, and a number of conceptual models were created in earlier research on the adoption of technology. However, the UTAUT model can only account for user satisfaction and the usage of the system as a modifying factor to mitigate individual effects. As a result, researchers try to include another variable.

In previous research, the Delone McLean model [4] was proposed because of its six-factor complexity, which included system quality, information quality, service quality, user satisfaction, system utilization, and institutional effect. This model was seen to be superior to the TAM model and the UTAUT model. Therefore, the advantages of the Delone McLean model are the greatest [4]. In the sphere of education, developing nations such as Indonesia, Malaysia, and Thailand have adopted numerous technologies, such as learning management systems (LMS). The purpose of this study is to identify the significant factors that influence the use of university LMS in relation to student satisfaction, using LMS as the object and extending the Delone McLean model by testing the self-efficacy factor. Incorporating computer self-efficacy (CSE) variables into the conceptual framework was a modification we made following a review of the best available literature.

A. Information Quality (IQ) and Student Satisfaction (SS)

Users receive information from information systems. Measures such as timeliness, correctness, completeness, consistency, and relevance can be used to assess the quality of system information [6]. The higher the information quality, the greater the user satisfaction with the system [7]. According to [8], to identify the quality of information, it will be seen how much the role of influence on student user satisfaction [8]. Furthermore, a previous study has demonstrated that information quality significantly impacts student LMS satisfaction [9]. To explore if the quality of information influences student satisfaction with the university

LMS, the first hypothesis states:

H1: Information quality (IQ) significantly influences student satisfaction (SS).

B. System Quality (SQ) and Student Satisfaction (SS)

System quality refers to the performance of the system as perceived by users [10]. According to [4] user satisfaction, technological achievement, and organizational and individual impact are good system quality indicators. Usability, responsiveness, availability, adaptability, and dependability are specific system quality components [5, 11]. A number of studies [8–10, 12] have revealed that system quality significantly impacts student satisfaction. The more satisfied students are with the LMS, the more accessible and reliable they believe it to be. The second hypothesis is as follow [12]:

H2: System quality (SQ) significantly influences student satisfaction (SS).

C. Service Quality (SeQ) and Student Satisfaction (SS)

According to [13] Noorman bin Masrek (2007), service quality is the overall quantity of support provided by a service provider.. According to [14] recent research, it refers to service characteristics such as responsiveness, availability, and efficacy. Previous studies [15] have found a correlation between service quality and student satisfaction. According to earlier studies [13], service quality predicts students' satisfaction. However, service quality has no bearing on student satisfaction. Based on these findings, universities' student satisfaction services are being evaluated. The third hypothesis is as follow:

H3: Service quality (SeQ) has a significant positive effect on Student Satisfaction (SS).

D. Computer Self-Efficacy (CSE) and Student Satisfaction (SS)

Self-efficacy is an individual's belief in students' ability to complete a task and achieve a certain level of performance with their talents; hence, self-efficacy beliefs influence how people motivate themselves and behave [16].

The original concept of self-efficacy included confidence in one's ability to use abilities such as computers and information technology. Later management information systems (MIS) researchers established computer self-efficacy (CSE) as a critical MIS study construct. It is defined as "an individual's perception of his or her ability to perform a task using a computer" [17]. Computer self-efficacy is positively associated with e-learning outcomes, as measured by average test scores in e-learning [18]. Among E-learners, self-efficacy and perceived system utility are positively related to perceived content value, course satisfaction, and course performance [19].

Other research has looked into the attitudes and behaviors that influence the use of course management systems. A significant positive link was discovered between self-efficacy and the intention to use e-learning technologies. Computer self-efficacy, achievement value, utility value, and intrinsic value were all significant predictors of persons' intention to continue utilizing web-based learning [20]. Self-efficacy, learner satisfaction, and perceived usefulness were discovered to have strong positive correlations [21]. Therefore, the fourth and fifth hypotheses are as follows:

H4: Computer self-efficacy (CSE) significantly influences student satisfaction (SS).

H5: Computer self-efficacy (CSE) significantly influences LMS usage (LU).

E. Student Satisfaction (SS) and LMS Usage (LU)

Many previous studies examined the relationship between user satisfaction and individual impact [22, 23], user satisfaction, and learning outcomes [24, 25]. These studies consistently demonstrate a positive correlation between user satisfaction and learning outcomes' efficacy. Therefore, the sixth hypothesis is as follows [26]:

H6: Student satisfaction (SS) has a positive effect on LMS usage (LU)

II. METHOD

A. Participants

The study involved 311 undergraduate students from two private Islamic universities in Jakarta, Indonesia. The responding students ranged in age from 18 to 24, with a 36% male to 64% female ratio based on random sampling. From May to July 2023, respondents completed the questionnaire via a Google Form link [27].

B. Data Collection

Students reported their LMS learning experiences in this section. The primary purpose of this research is to determine how Computer Self-Efficacy (CSE) affects LMS utilization and student satisfaction. Using the research findings, the performance of the LMS can be examined, and virtual learning can be improved [28].

In this study, researchers collaborated with the university to disseminate the questionnaires to the students, and it only took the respondents 10-15 minutes to complete the questions. Since there were repeat respondents, only 311 respondents matched the criteria. The questionnaire measured 21 model constructs using a Likert scale of 1 (strongly disagree) to 5 (strongly agree) [29].

C. Measurementss

This study analyzed data using the Structural Equation Modeling (SEM) approach and the Smart PLS version 3.0 program [30]. PLS is a well-known method for evaluating structural model path coefficients that have gained popularity in marketing research over the last decade due to its capacity to model latent structures under irregularity and small to medium sample sizes [31]. PLS research has been undertaken and found to be an appropriate component of this study. Furthermore, the PLS algorithm mechanism was utilized to evaluate the set, weights, and path coefficients and determine the significance of the hypothesis using the bootstrap method (5000 samples). This measurement model is accurate and effective for empirical validation processes [31].

III. RESULTS

A. Measurement Model Evaluation

In this step, the measurement model (outer model) is evaluated to explain and discover the relationship between the latent variable and the indicators. This is related to the

instrument's validity and reliability [26]. The validity of the instruments was assessed using discriminant and convergent

validity. According to Table 1, the instruments' validity was assessed using discriminant and convergent validity.

Table 1. Measurement constructs

Construct	Item	Statement
Informaton Quality	IQ1	I can obtain accurate information from LMS.
	IQ2	The LMS can provide me with the information I need to accomplish my duties.
	IQ3	LMS can provide updated task-related information.
	IQ4	The LMS can provide me with up-to-date task information.
System Quality	SQ1	The LMS features an intuitive user interface.
	SQ2	The LMS provides time and location flexibility.
	SQ3	The LMS contains effective communication language.
	SQ4	LMS is readily accessible whenever I need to use it.
Service Quality	SeQ1	Training on the LMS's operation is sufficient.
	SeQ2	Multiple channels are available for communicating with the technicians.
	SeQ3	The provided training can enhance my ability to utilize LMS.
	SeQ4	In general, the university provides sufficient support for LMS usage.
Computer Self-Efficacy	CSE1	I am comfortable using a web browser.
	CSE2	I am confident completing tests online.
	CSE3	I am comfortable uploading/downloading files.
Students Satisfaction	SS1	The LMS applications have met my expectations.
	SS2	The LMS application is of good quality.
	SS3	The LMS application meets my requirements.
LMS Usage	LU1	Utilizing LMS is a wise decision.
	LU2	Working with the LMS is enjoyable.
	LU3	I enjoy working with LMS.

B. Construct Reliability, Convergent Validity, Discriminant Validity

Previous research results [27] were analyzed by calculating the loading factor value of each indicator in the displayed structure.

According to Table 2, convergent validity is inferred if all indicators have loading factor values that satisfy the validity requirements and the value is greater than 0.70 (>0.70). The IQ1 and CSE3 indicator loadings are less than the threshold value (<0.70), requiring their elimination. This finding is consistent with Ali's (2018) argument that any indication is good if its loading factor is greater than 0.70 [28].

Following the analysis of the loading factor data, we proceed to the interpretation of Composite Reliability (CR). A limit value of more than 0.6 is appropriate, while a value >0.7 is acceptable. The average occurrence (AVE) value is another indicator of convergent validity. The AVE value defines the degree of variation or set of manifest variables that a latent concept may have. As a result, the wider the variance or range of manifest variables that a latent partner can incorporate, the more thoroughly reflected the manifest variable will be in its latent construct.

When examining convergent validity parameters, AVE is recommended. A minimum AVE of 0.5 implies that convergent validity is a reliable indication. On average, the latent variable can explain more than half of the predictor variance. The AVE value is derived from the sum of the loading factor's squares minus the error.

Table 2 shows that the composite reliability and AVE values exceed the resultant AVE value for each latent variable by more than 0.5. This finding implies that both of these

factors are highly reliable.

Table 2. Measurement model

Construct	Item	Factor Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)
Information Quality	IQ2	0.773	0.888	0.727
	IQ3	0.887		
	IQ4	0.892		
System Quality	SQ1	0.831	0.872	0.630
	SQ2	0.736		
	SQ3	0.812		
	SQ4	0.793		
Service Quality	SeQ1	0.759	0.890	0.670
	SeQ2	0.804		
	SeQ3	0.872		
	SeQ4	0.836		
Computer Self-Efficacy	CSE1	0.917	0.912	0.838
	CSE2	0.913		
Students Satisfaction	SS1	0.904	0.917	0.787
	SS2	0.890		
	SS3	0.867		
LMS Usage	LU1	0.752	0.890	0.731
	LU2	0.907		
	LU3	0.897		

The discriminant validity of the heterotrait-monotrait ratio (HTMT) was applied to validate the measurement model. Previous research has used 0.90 as the maximum threshold of the HTMT ratio constructs [29, 30]. Table 3 shows the validation of the measurement model concerning this threshold value.

Table 3. Discriminant validity of Heterotrait-Monotrait Ratio (HTMT)

Construct	Computer Self Efficacy	Information Quality	LMS Usage	Service Quality	Student Satisfaction	System Quality
Computer Self Efficacy						
Information Quality	0.772					
LMS Usage	0.904	0.902				
Service Quality	0.916	0.864	1.092			
Student Satisfaction	0.632	0.976	0.836	0.729		
System Quality	0.795	0.833	0.959	0.832	0.973	

C. Structural Model Evaluation

After establishing the measurement model, the second stage in the two-step statistical technique for modeling the PLS-SEM model is to build the structural model. The path coefficients and explained variance are included in the structural model. After selecting 5000 random sub-samples with replacement from one original sample, the regression coefficients (or beta values) were refined using a bootstrapping method by generating bootstrap standard errors.

The process must be run constantly 5000 times [29]. The PLS path model was then estimated using these subsamples.

Table 4 summarizes the findings concerning the relevance of the routes corresponding to hypotheses H1, H2, H3, H4, H5, and H6. The data reveal that these pathways' 5% and 95% confidence interval values support hypotheses H1, H2, H5, and H6. However, H3 and H4 are rejected since the confidence interval values are less than zero for one-tailed testing with p-values of 0.05.

Table 4. Hypothesis testing

Hypothesis	Path	Std.Beta	Std.Error	T-value	Bias	Confidence Interval		Decision
						5.0%	95.0%	
H1	Information Quality → Student Satisfaction	0.581	0.051	11.406	0.002	0.490	0.658	Supported
H2	System Quality → Student Satisfaction	0.586	0.050	11.824	-0.003	0.506	0.668	Supported
H3	Service Quality → Student Satisfaction	-0.087	0.045	1.933	0.002	-0.162	-0.012	Rejected
H4	Computer Self Efficacy → Student Satisfaction	-0.130	0.042	3.088	0.001	-0.198	-0.060	Rejected
H5	Computer Self Efficacy → LMS Usage	0.501	0.052	9.570	-0.001	0.416	0.588	Supported
H6	Student Satisfaction → LMS Usage	0.441	0.057	7.788	-0.000	0.344	0.529	Supported

Note: $p < 0.05$ (1-tailed test)

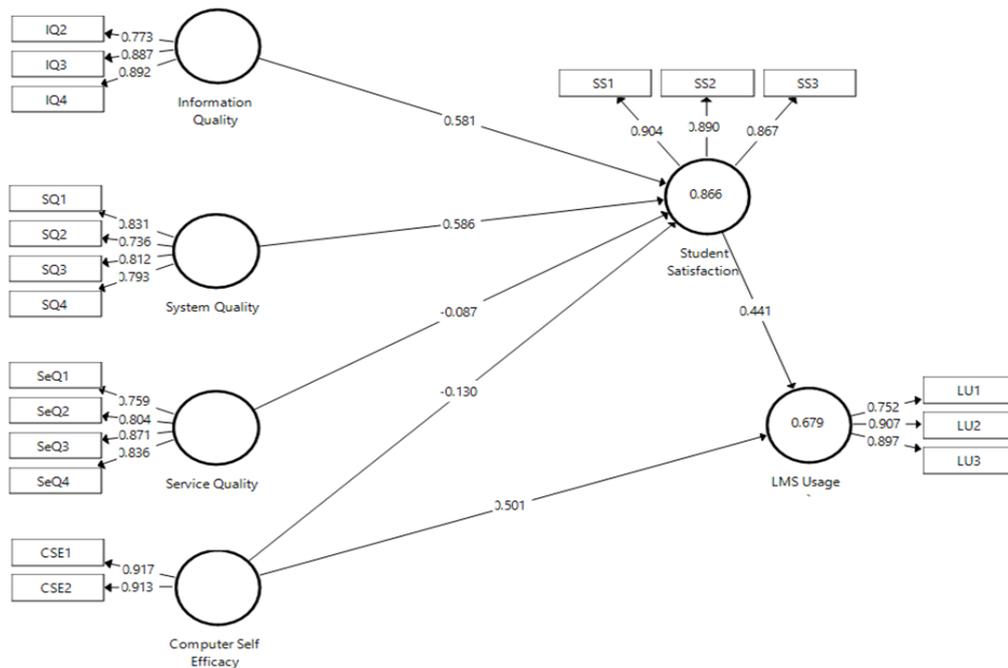


Fig. 1. Path analysis.

The coefficient of determination (R^2) is frequently used to analyze the model's predictive capacity and structural model. It is the squared correlation between the actual and expected

values of an endogenous building. The coefficient represents the sum of the exogenous variables' effects on the latent endogenous variables. Because R^2 has a range of 0–1, it is

difficult to construct an exact rule of thumb. Higher numbers indicate higher prediction points. As a result, the value of student satisfaction and LMS usage is determined by the complexity of the model and the research discipline.

Table 5. The coefficient of determination (R^2)

	R^2	R^2 Adjusted
LMS Usage	0.679	0.677
Student Satisfaction	0.866	0.864

The coefficient of determination (R^2) in Fig. 1 and Table 5 verifies the research's model. This coefficient measures the model's predictive ability and is computed as the squared correlation between the actual and predicted values of a specific endogenous construct [31]. Furthermore, the R^2 value indicates the percentage of variation explained by each model construct. R^2 values of 0.75, 0.50, and 0.25 for endogenous constructs can be classified as significant, moderate, and insignificant [32].

The R^2 values of the dependent constructs, student satisfaction, and LMS usage, are displayed in Fig. 1 and Table 5. The model explains 86.6% of the variance in student satisfaction and 67.9% of the variance in LMS usage. The R^2 values of the two dependent constructs (student satisfaction and LMS usage) are 0.866 and 0.679, respectively, which are considered sufficient [31]. Fig. 1 also depicts the structural model with path coefficients for each path (hypothesized relationship) with a significant level and coefficient of determination (R^2).

IV. DISCUSSION

Model validity and reliability tests show that the established constructs are reliable and valid, which helps to verify the accuracy of the PLS-SEM-derived measurement model. Meanwhile, validation of the structural model shows that the generated model is not only a strong fit but also has exceptional predictive significance.

Hypotheses H1, H2, H5, and H6 are supported by the established structural model's results in direct effects. H3 and H4 were, however, rejected. The findings demonstrate that information and system quality have a direct positive impact on student happiness. LMS utilization is also influenced by computer self-efficacy and student satisfaction.

The value obtained for testing the first hypothesis (H1) is greater than zero within a confidence interval of 5% (0.490) and 95% (0.658), indicating that the results are supported. The beneficial influence of information quality on student satisfaction happens when university LMS is used. Previous research supports this finding [33]. Similarly, the other study discovered that information quality influences student satisfaction [34, 35]. However, according to the findings of another study, information quality does not affect student satisfaction due to internal user variables [36].

The value above zero is achieved at a confidence interval of 5% (0.506) and 95% (0.668) for testing the second hypothesis (H2), indicating that the results are supported. Student satisfaction was found to be influenced by system quality. Johnson *et al.* [19] produced similar results, demonstrating that good system quality of LMS technology benefits user satisfaction [12]. Other research has found that system quality

influences student satisfaction [37]. However, a study by Mtebe and Raisamo [38] found that system quality does not affect student satisfaction. Quality feasibility aspects heavily influence user satisfaction outcomes.

The third hypothesis (H3) is rejected since a value above zero is obtained at a confidence interval of 5% (-0.612) and 95% (-0.012). According to Mtebe and Raisamo [38], service quality has little effect on user satisfaction because user understanding of utilizing the LMS is inadequate [38]. Johnson *et al.* [19] discovered the same thing: the limited menu of supporting services dissatisfied people with the LMS. However, according to Alzahrani and Seth [3], the skill component of using LMS technology determines student happiness with LMS technology. In general, training for these users is significant in some universities. The same study found that a person's knowledge attitude influences their satisfaction with technology [34].

The fourth hypothesis (H4) is rejected when a value greater than zero is achieved at a confidence interval of 5% (-0.198) and 95% (-0.060). According to Ghazal *et al.* [12], computer self-efficacy influences student satisfaction with the LMS because it facilitates communication with operators and instruction to use the LMS, hence enhancing student skills to operate the LMS is needed [5, 39]. The same thing was also found by [40] and [5] the factors of comprehension and skills in mastering technology immediately affect one's behavior in using the LMS, which has an impact on the level of satisfaction [41]. However, according to Eom [34], self-efficacy factor has no effect on satisfaction using the LMS [42].

The value above zero is achieved at a confidence interval of 5% (0.418) and 95% (0.588) for testing the fifth hypothesis (H5), indicating that the results are supported. As a result, Computer Self-Efficacy (CSE) influences LMS utilization. According to Ghazal *et al.* [5], students' confidence in using the LMS impacts whether or not they continue to utilize the LMS [43–45].

The value above zero is achieved at a confidence interval of 5% (0.344) and 95% (0.529) for testing the sixth hypothesis (H6), indicating that the results are supported. LMS usage is influenced by user satisfaction. Learner satisfaction, according to Aldholay *et al.* [46], determines continuous usage of the LMS in online learning [40, 46].

V. CONCLUSION

Based on the review of the literature and the findings of the research, it is concluded that there are numerous elements that influence learner satisfaction with using an LMS. The direct testing of six hypotheses reveals that four of them are supported. The findings show that information quality, system quality, and quality all have an impact on student satisfaction. While CSE and satisfaction have an impact on LMS utilization. We conclude that this study was a success. However, the rejected results require further investigation to demonstrate the impact of service quality and CSE on student satisfaction.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Khoerul Umam and Zulherman conducted research, and write the papers, Irdalisa, Wati Sukmawati analyzed data, Supriyansyah adding some references. All authors had approved the final version.

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REFERENCES

- [1] A. Aldiab, H. Chowdhury, A. Kootsookos, F. Alam, and H. Allhibi, "Utilization of Learning Management Systems (LMSs) in higher education system: A case review for Saudi Arabia," *Energy Procedia*, vol. 160, no. 2018, pp. 731–737, 2019. doi: 10.1016/j.egypro.2019.02.186
- [2] T. Soffer and R. Nachmias, "Effectiveness of learning in online academic courses compared with face-to-face courses in higher education," *J. Comput. Assist. Learn.*, vol. 34, no. 5, pp. 534–543, 2018. doi: 10.1111/jcal.12258
- [3] L. Alzahrani and K. P. Seth, "Factors influencing students' satisfaction with continuous use of learning management systems during the COVID-19 pandemic: An empirical study," *Educ. Inf. Technol.*, vol. 26, no. 6, pp. 6787–6805, 2021. doi: 10.1007/s10639-021-10492-5
- [4] A. Jeyaraj, "DeLone & McLean models of information system success: Critical meta-review and research directions," *Int. J. Inf. Manage.*, vol. 54, no. November 2019, 102139, 2020. doi: 10.1016/j.ijinfomgt.2020.102139
- [5] S. Ghazal, H. Aldowah, I. Umar, and B. Bervell, "Acceptance and satisfaction of learning management system enabled blended learning based on a modified DeLone-McLean information system success model," *Int. J. Inf. Technol. Proj. Manage.*, vol. 9, no. 3, pp. 52–71, 2018. doi: 10.4018/IJITPM.2018070104
- [6] W. H. DeLone and E. R. McLean, "The DeLone and McLean model of information systems success: A ten-year update," *J. Manag. Inf. Syst.*, vol. 19, no. 4, pp. 9–30, 2003. doi: 10.1080/07421222.2003.11045748
- [7] M. Ghasemaghaei and K. Hassanein, "Online information quality and consumer satisfaction: The moderating roles of contextual factors - A meta-analysis," *Inf. Manage.*, vol. 52, no. 8, pp. 965–981, 2015. doi: 10.1016/j.im.2015.07.001
- [8] H. Al-Samarraie, H. Selim, T. Teo, and F. Zaqout, "Isolation and distinctiveness in the design of e-learning systems influence user preferences," *Interact. Learn. Environ.*, vol. 25, no. 4, pp. 452–466, 2017. doi: 10.1080/10494820.2016.1138313
- [9] Q. Hammouri and E. Abu-Shanab, "Exploring factors affecting users' satisfaction toward e-learning systems," *Int. J. Inf. Commun. Technol. Educ.*, vol. 14, no. 1, pp. 44–57, 2018. doi: 10.4018/IJICTE.2018010104
- [10] S. M. Jafari, S. F. Salem, M. S. Moaddab, and S. O. Salem, "Learning Management System (LMS) success: An investigation among the university students," *2015 IEEE Conf. e-Learning, e-Management e-Services, IC3e 2015*, no. August, pp. 64–69, 2016. doi: 10.1109/IC3e.2015.7403488
- [11] E. S. Alim, K. Umam, and S. Wijirahayu, *The Implementation of Blended Learning Instruction by Utilizing WeChat Application*, 2016.
- [12] S. Ghazal, H. Aldowah, and I. Umar, "Critical factors to learning management system acceptance and satisfaction in a blended learning environment," *Lect. Notes Data Eng. Commun. Technol.*, vol. 5, no. April 2019, pp. 688–698, 2018. doi: 10.1007/978-3-319-59427-9_71
- [13] J. S. Mtebe and C. Raphael, "Key factors in learners' satisfaction with the e-learning system at the University of Dar es Salaam, Tanzania," *Australas. J. Educ. Technol.*, vol. 34, no. 4, pp. 107–122, 2018. doi: 10.14742/ajet.2993
- [14] E. Lwoga, "Critical success factors for adoption of web-based learning management systems in Tanzania Edda Tandi Lwoga Muhimbili University of Health and Allied Sciences, Tanzania," *Int. J. Educ. Dev. using Inf. Commun. Technol.*, vol. 10, no. 1, pp. 4–21, 2014.
- [15] M. N. Bin Masrek, "Measuring campus portal effectiveness and the contributing factors," *Campus-Wide Inf. Syst.*, vol. 24, no. 5, pp. 342–354, 2007. doi: 10.1108/10650740710835760
- [16] A. Bandura, "Self-Efficacy," *Wiley Encycl. Personal. Individ. Differ.*, no. 1994, pp. 387–391, 1994. doi: 10.1002/9781118970843.ch243
- [17] D. R. Compeau and C. A. Higgins, "Computer self-efficacy: Measure And initial development of a test," *MIS Q.*, vol. 19, no. 2, pp. 189–211, 2017.
- [18] M. J. Simmering, C. Posey, and G. Piccoli, "Computer self-efficacy and motivation to learn in a self-directed online course," *Decis. Sci. J. Innov. Educ.*, vol. 7, no. 1, pp. 99–121, 2009. doi: 10.1111/j.1540-4609.2008.00207.x
- [19] R. D. Johnson, S. Hornik, and E. Salas, "An empirical examination of factors contributing to the creation of successful e-learning environments," *Int. J. Hum. Comput. Stud.*, vol. 66, no. 5, pp. 356–369, 2008. doi: 10.1016/j.ijhcs.2007.11.003
- [20] C. M. Chiu and E. T. G. Wang, "Understanding Web-based learning continuance intention: The role of subjective task value," *Inf. Manage.*, vol. 45, no. 3, pp. 194–201, 2008. doi: 10.1016/j.im.2008.02.003
- [21] S. S. Liaw and H. M. Huang, "Perceived satisfaction, perceived usefulness and interactive learning environments as predictors to self-regulation in e-learning environments," *Comput. Educ.*, vol. 60, no. 1, pp. 14–24, 2013. doi: 10.1016/j.compedu.2012.07.015
- [22] B. W. J. Doll, "The measurement of end-user computing satisfaction," vol. 12, no. 2, pp. 259–274, 2013.
- [23] A. Rai, S. S. Lang, and R. B. Welker, "Assessing the validity of IS success models: An empirical test and theoretical analysis," *Inf. Syst. Res.*, vol. 13, no. 1, pp. 50–69, 2002. doi: 10.1287/isre.13.1.50.96
- [24] R. B. Ikhsan, L. A. Saraswati, B. G. Muchardie, Vional, and A. Susilo, "The determinants of students' perceived learning outcomes and satisfaction in BINUS online learning," in *Proc. 2019 5th Int. Conf. New Media Stud. CONMEDIA 2019*, no. April, pp. 68–73, 2019. doi: 10.1109/CONMEDIA46929.2019.8981813
- [25] S. Maarif, K. Umam, J. Soebagyo, and T. R. Pradipta, "Critical review on mathematics virtual classroom practice in private university," *Int. J. Nonlinear Anal. Appl.*, vol. 13, no. 1, pp. 975–982, 2022. doi: 10.22075/ijnaa.2022.5616
- [26] S. Tehseen, S. Sajilan, K. Gadar, and T. Ramayah, "Assessing cultural orientation as a reflective-formative second order construct-A recent PLS-SEM approach," *Rev. Integr. Bus. Econ. Res.*, vol. 6, no. 2, pp. 38–63, 2017.
- [27] J. H. Cheah, M. Sarstedt, C. M. Ringle, T. Ramayah, and H. Ting, "Convergent validity assessment of formatively measured constructs in PLS-SEM: On using single-item versus multi-item measures in redundancy analyses," *Int. J. Contemp. Hosp. Manag.*, vol. 30, no. 11, pp. 3192–3210, 2018. doi: 10.1108/IJCHM-10-2017-0649
- [28] J. F. Hair, M. Sarstedt, C. M. Ringle, and J. A. Mena, "An assessment of the use of partial least squares structural equation modeling in marketing research," *J. Acad. Mark. Sci.*, vol. 40, no. 3, pp. 414–433, 2012. doi: 10.1007/s11747-011-0261-6
- [29] J. F. H. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "The results of PLS-SEM article information," *Eur. Bus. Rev.*, vol. 31, no. 1, pp. 2–24, 2018.
- [30] A. H. Gold, A. Malhotra, and A. H. Segars, "Knowledge management: An organizational capabilities perspective," *J. Manag. Inf. Syst.*, vol. 18, no. 1, pp. 185–214, 2001. doi: 10.1080/07421222.2001.11045669
- [31] D. J. Ketchen, *A Primer on Partial Least Squares Structural Equation Modeling*, vol. 46, no. 1–2, 2013.
- [32] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling*, vol. 46, no. 1–2, 2013.
- [33] M. A. Alkhateeb and R. A. Abdalla, "Factors influencing student satisfaction towards using learning management system moodle," *Int. J. Inf. Commun. Technol. Educ.*, vol. 17, no. 1, pp. 138–153, 2021. doi: 10.4018/IJICTE.2021010109
- [34] J. Ohliati and B. S. Abbas, "Measuring students satisfaction in using learning management system," *Int. J. Emerg. Technol. Learn.*, vol. 14, no. 4, pp. 180–189, 2019. doi: 10.3991/ijet.v14.i04.9427
- [35] B. Bunyamin, K. Umam, and L. Lismawati, "Critical review of m-learning in total quality management classroom practice in an Indonesian private university," *Int. J. Interact. Mob. Technol.*, vol. 14, no. 20, pp. 76–90, 2020. doi: 10.3991/ijim.v14i20.15141
- [36] Y. C. Togar Alam Napitupulu, "Evaluation of student satisfaction in using the learning management system for online learning at XYZ University," *Turkish J. Comput. Math. Educ.*, vol. 12, no. 6, pp. 2810–2816, 2021. doi: 10.17762/turcomat.v12i6.5788

- [37] S. B. Eom, "Effects of LMS, self-efficacy, and self-regulated learning on LMS effectiveness in business education," *J. Int. Educ. Bus.*, vol. 5, no. 2, pp. 129–144, 2012. doi: 10.1108/18363261211281744
- [38] J. S. Mtebe and R. Raisamo, "A model for assessing learning management system success in higher education in sub-saharan Countries," *Electron. J. Inf. Syst. Dev. Ctries.*, vol. 61, no. 1, 2014. doi: 10.1002/j.1681-4835.2014.tb00436.x
- [39] F. G. Barbeite and E. M. Weiss, "Computer self-efficacy and anxiety scales for an Internet sample: Testing measurement equivalence of existing measures and development of new scales," *Comput. Human Behav.*, vol. 20, no. 1, pp. 1–15, 2004. doi: 10.1016/S0747-5632(03)00049-9
- [40] A. M. Shaltoni, H. Khraim, A. Abuhamad, and M. Amer, "The international journal of information and learning technology article information," *Int. J. Inf. Learn. Technol.*, vol. 32, no. 2, pp. 109–123, 2015.
- [41] R. Prifti, "Self-efficacy and student satisfaction in the context of blended learning courses," *Open Learn.*, vol. 37, no. 2, pp. 111–125, 2022. doi: 10.1080/02680513.2020.1755642
- [42] S. B. Eom, "Understanding e-learners' satisfaction with learning management systems," *Bull. Tech. Comm. Learn. Technol.*, vol. 16, no. 2–3, pp. 10–13, 2014.
- [43] A. Aldholay, Z. Abdullah, O. Isaac, and A. M. Mutahar, "Perspective of Yemeni students on use of online learning: Extending the information systems success model with transformational leadership and compatibility," *Inf. Technol. People*, vol. 33, no. 1, pp. 106–128, 2020. doi: 10.1108/ITP-02-2018-0095
- [44] K. Umam, T. Nusantara, I. N. Parta, E. Hidayanto, and H. Mulyono, "An application of flipped classroom in mathematics teacher education programme," *Int. J. Interact. Mob. Technol.*, vol. 13, no. 3, 2019. doi: 10.3991/ijim.v13i03.10207
- [45] A. Fatayan, S. Ayu, and K. Umam, "Enhancing learning motivation of university students in Indonesia with the RADEC model and Google Earth," *World Trans. Eng. Technol. Educ.*, vol. 21, no. 2, pp. 128–133, 2023.
- [46] A. H. Aldholay, O. Isaac, Z. Abdullah, and T. Ramayah, "The role of transformational leadership as a mediating variable in DeLone and McLean information system success model: The context of online learning usage in Yemen," *Telemat. Informatics*, vol. 35, no. 5, pp. 1421–1437, 2018. doi: 10.1016/j.tele.2018.03.012

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