International Journal Of Humanities Education And Social Sciences ***(IJHESS)*** *E-ISSN:* **2808-1765**
Volume 5, Number 2, October 2025, *Page. 1020 – 1032*
Email : editorijhess@gmail.com

The Influence of E-Learning Utilization and LMS Quality on Student Achievement through Online Interaction (Open University Case Study in Online Learning for Even Semester 2024)

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Abstract

The urgency of this research lies in the need to optimize the use of e-learning and the LMS Moodle to improve student academic achievement at Universitas Terbuka. Although the system is already running, gaps are still found in student engagement, the quality of online interactions, and perceptions of the LMS. This research is important to address the challenges of implementing online learning to be more effective, equitable, and efficient. The purpose of this study is to analyze the effect of e-learning utilization and LMS quality on student achievement by mediating online interactions at Universitas Terbuka. This study uses the PLS-SEM-based Path Analysis method with the help of SmartPLS software to analyze the causal relationship between e-learning utilization, LMS quality, online interactions, and student achievement. The instrument was tested for validity and reliability through outer loading values, AVE, Cronbach's Alpha, and Composite Reliability before conducting structural analysis. The results of the analysis aim to reveal the direct and indirect influences between variables and test their significance through bootstrapping techniques. This study produced six main findings. First, active e-learning utilization had a very strong and significant effect on perceived LMS quality ($\beta = 0.914$; $p = 0.000$), indicating that the more frequently students used the LMS, the higher their assessment of the system's quality. Second, e-learning utilization did not directly affect academic achievement ($\beta = –0.019$; $p = 0.893$), indicating that frequency of use does not necessarily impact academic achievement without meaningful engagement. Third, e-learning utilization had a positive effect on online interaction ($\beta = 0.478$; $p = 0.001$), indicating that active students were more frequently involved in digital forums and communication. Fourth, LMS quality also had a significant effect on online interaction ($\beta = 0.487$; $p = 0.000$), reinforcing the role of system features and convenience in supporting online communication. Fifth, LMS quality had a positive effect on student achievement ($\beta = 0.234$; $p = 0.049$), indicating that an effective LMS supports academic achievement. Sixth, online interaction has the strongest influence on student achievement ($\beta = 0.767$; $p = 0.000$), proving that active involvement in digital learning is very important in determining learning success.

Keywords: E-Learning, LMS Quality, Student Achievement, Online Interaction

INTRODUCTION

Education is a basic right guaranteed by Article 31 of the 1945 Constitution, which affirms that every citizen has the right to education, and the government is obliged to organize a national education system that enhances faith, piety, and noble character. To support this, Law No. 20 of 2003 concerning the National Education System mandates that education must be administered fairly and democratically, including through the use of technology (Borup et al., 2014).

In the digital era, higher education needs to respond to developments in information and communication technology by adopting online learning systems. LMSs like Moodle are the backbone in supporting learning flexibility and accessibility (DeLone & McLean, 2003). Moodle, as an open-source LMS, has been widely adopted, including by the Open University (UT) in Indonesia (Garrison et al., 2000). Bibliometric data from 155 articles shows Moodle as the most popular LMS, with users increasing from 78 million (2015) to 294 million (2021), indicating its strategic role in online learning (Jo et al., 2017).

Moodle's effectiveness is evident in student activity. The "Digital Footprints of Academic Success" study showed that students who actively used Moodle forums on weekends achieved

10% higher academic grades. Activities such as module visits, forum participation, and time spent using the LMS are important indicators in predicting achievement (Martin et al., 2020). In Indonesia, research at Indraprasta PGRI University with 275 respondents showed that 43% of students found Moodle effective due to its structured flow and ease of navigation (Muslimin & Widodo, 2021).

Another study at UIN Makassar noted that Moodle use and learning motivation significantly influenced learning outcomes, with an R^2 of 0.606. This means that 60% of the variation in learning achievement is explained by these two factors (Putra & Wahyuni, 2021). At PKBM Darul Fiqri, the use of Moodle modules was also shown to improve achievement during the pandemic. Meanwhile, a study at UIN Maulana Malik Ibrahim showed an increase in Moodle usage from 18.5% to 51% in one semester, although user satisfaction scores still varied, with student-lecturer communication only reaching a score of 3.18 on a scale of 5 (Sher, 2009). A usability study at the BPS Training Center also showed that Moodle was quite optimal from a technical perspective, but needed to be supported by effective learning and communication strategies (Sun et al., 2008).

In the context of UT, Moodle has long been the primary learning management system (LMS). The even semester of 2024 marked its full implementation, including in the Faculty of Economics. However, academic evaluations show significant variation in student achievement. This indicates that the utilization of LMS and e-learning is suboptimal, due to differences in digital skills, LMS quality, and intensity of online interactions.

Ideally (Das Sollen), a high-quality, optimally utilized LMS should improve student achievement. An LMS should not only provide content but also provide a space for interaction, reflection, and feedback. Within the framework of Freedom to Learn, technology should encourage active and collaborative learning.

However, there are several important gaps. First, not all students actively utilize LMSs. Many simply download materials without further interaction. Second, the quality of LMSs from a user perspective has not been widely researched locally, particularly regarding navigational convenience, access speed, and features. Third, online interaction between students and lecturers is still minimal. In face-to-face learning, direct interaction can deepen understanding. In online learning, the success of interactions depends heavily on the infrastructure and awareness of both parties. Few studies have examined online interaction as a mediating variable between e-learning and academic achievement.

Finally, there is a local empirical gap. While global research on e-learning and LMS is quite extensive, contextual studies in Indonesia, particularly at UT, are still limited. This is despite UT's unique characteristics as an open higher education institution. This study aims to bridge this gap by examining the influence of e-learning utilization and LMS quality on student achievement, mediated by online interactions.

RESEARCH METHODS

This study used the Partial Least Square – Structural Equation Modeling (PLS-SEM) based Path Analysis method , processed using SmartPLS software. This method was chosen because it is able to analyze causal relationships between variables, including direct and indirect influences, as well as the role of mediating variables, such as online interaction (Z) in the relationship between e-learning utilization (X_1) and LMS quality (X_2) on student achievement (Y). As previously explained, there are four main variables:

Table 1 Variables and Indicators

Variables	Symbol	Type	Indicator
Utilization of E-Learning	X_1	Independent variable	Access frequency, duration, discussion forum, assignment upload
LMS Quality	X_2	Independent variable	Navigation, access speed, user-friendliness, stability, features
Online Interaction	Z	Mediation	Forum participation, communication, lecturer feedback, synchronous attendance
Student Achievement	Y	Bound	GPA, final assignment grades, online UAS grades, CPL achievements

This research focused on students at the Faculty of Economics, Universitas Terbuka (UT), given its large active student population and prominent online learning characteristics. The location was selected based on its direct relevance to the study's objective: the use of the Moodle Learning Management System (LMS) for distance learning in the even semester of 2024.

The population in this study included all active students at the Faculty of Economics, Universitas Terbuka (UT) currently studying in that semester. However, due to resource limitations and to ensure data validity, not the entire population was included as respondents. Therefore, the researcher used purposive sampling , a sampling technique based on specific criteria deemed relevant to the research objectives.

The inclusion criteria set in sampling are as follows: (1) students have participated in full online learning using the Moodle LMS platform , and (2) students have completed at least two courses that have active online activities, such as discussion forums, online assignment submissions , and synchronous sessions. With these criteria, it is expected that respondents truly have adequate experience in using LMS so that they can provide accurate and reflective answers to the variables studied.

Based on the calculation of the minimum sample requirement in the Partial Least Squares Structural Equation Modeling (PLS-SEM) method, an adequate number of respondents is at least 10 times the maximum number of indicators in a construct. Considering the complexity of the model and the number of indicators in this study, the sample size was determined to be 150 students. This number is considered sufficient to produce stable model estimates that can be statistically tested well using the SmartPLS application.

Through this planned sampling approach, it is hoped that the data obtained will be able to represent students' experiences in using Moodle-based e-learning in a representative manner, while also enabling analysis of the relationships between variables to be carried out validly and reliably.

Before further analysis is conducted, the research instrument, the questionnaire, must be tested to ensure that the measurement tool meets validity and reliability criteria. Validity testing aims to ensure that each indicator in the questionnaire effectively measures the intended construct, while reliability testing is used to assess the consistency or stability of measurement results between items within a single variable.

In the context of this research, validity testing was conducted using the Outer Loading approach in the PLS-SEM measurement model. The ideal outer loading value is greater than 0.7, indicating that the indicator significantly contributes to the construct being measured. Indicators with values below this threshold will be further evaluated to determine whether they need to be removed or revised.

Next, construct reliability tests were conducted using two main methods: Cronbach's Alpha and Composite Reliability (CR). The criteria used to determine good reliability are a

Cronbach's Alpha value of ≥ 0.7, and a CR of at least 0.7. These values indicate that each construct has a high level of internal consistency and is suitable for further analysis.

Furthermore, to ensure convergent validity, the Average Variance Extracted (AVE) measure is used. An AVE value of ≥ 0.5 indicates that more than 50% of the indicator's variance can be explained by the measured construct, thus meeting convergent validity. If a construct has an AVE below this threshold, it is deemed insufficiently representative of its indicators as a whole.

After the instrument is declared valid and reliable, the next step is data analysis using SmartPLS software version 4. SmartPLS is an analysis tool based on Partial Least Squares Structural Equation Modeling (PLS-SEM) which is very suitable for explanatory research with complex models and relatively moderate sample sizes such as in this study.

The analysis process is carried out in two main stages. The first stage is the analysis of the measurement model (outer model), which evaluates the indicators against their respective constructs, including examining the outer loading values, Cronbach's Alpha, Composite Reliability, and AVE. This stage is crucial to ensure that the measurement model has adequate statistical quality.

After the outer model meets the validity and reliability criteria, the process continues to the second stage, namely structural model analysis (inner model). At this stage, the relationships between latent variables are analyzed using path coefficient tests , statistical significance tests using bootstrapping, and coefficient of determination (R^2) analysis. This inner model is used to answer the research problem and test the previously formulated research hypotheses.

With this systematic and data-based analysis procedure, it is hoped that the research results will be able to accurately describe the extent to which the use of e-learning and the quality of LMS influence student achievement, both directly and through online interaction mediation. Path Analysis Formula (SEM PLS): The basic SEM-PLS model can be mathematically expressed as:

Y=β1X1+β2X2+β3Z+εY = $\beta_1 X_1 + \beta_2 X_2 + \beta_3 Z + \varepsilon$ Z=β4X1+β5X2+εZ = $\beta_4 X_1 + \beta_5 X_2 + \varepsilon$

Where:

- YY: Student Achievement
- X1X_1: Utilization of E-Learning
- X2X_2: LMS Quality
- ZZ: Online Interaction (mediator)
- ββ: Path Coefficient
- εε: Error/Residual

Path Significance Test (Bootstrapping)

This step is used to test:

- Direct Effect: The direct influence of X_1 and X_2 on Y
- Indirect Effect: Indirect influence through Z
- Total Effect: Combination of both

The results of the significance test are determined by the value:

- T-statistic > 1.96 (significant at $\alpha = 5\%$). P-value < 0.05

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RESULT AND DISCUSSION

The measurement model used to test validity and reliability, and includes the coefficient of determination and path coefficients from the structural equation model, is presented in Figure 1 below.

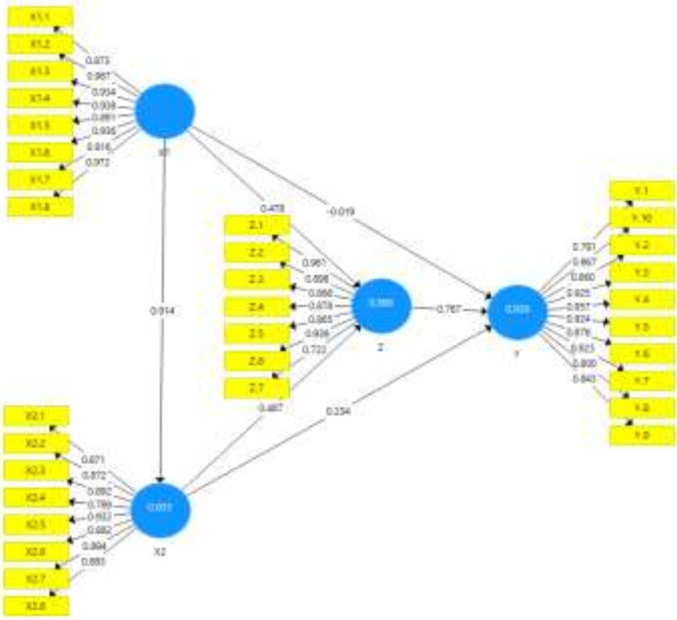

Figure 1 Outer Model SmartPLS
Source: Processed Data by Researcher, 2025

Structural Testing Model (Inner Model)

Coefficient Determination (R2)

The coefficient of determination (R-squared) is used to measure the extent to which an independent variable influences the dependent variable in a model. According to Chin, an R2 value above 0.67 for a dependent latent variable indicates that the independent variable's influence on the dependent variable can be categorized as good. If the R2 value is in the range of 0.33 to 0.67, then the influence category is moderate, while an R2 value between 0.19 and 0.33 is categorized as weak. Based on data analysis conducted using SmartPLS 3.0, the R-Square values obtained are as follows:

Table 1 Coefficient of Determination

Model	R	R Square
With	.877a	0.769
And	.804a	0.64 6

Source: Data Processed by Researchers, 2025

The R-Square value table is used to determine the magnitude of the influence of the independent variables on the dependent variable in this study. Based on the analysis results using SmartPLS, the R-Square (R^2) values obtained for each dependent variable are as follows:

First, the R-Square value for the Online Interaction (Z) variable of 0.769 indicates that 76.9% of the variation in online interactions can be explained by the independent variables, namely E-Learning Utilization (X_1) and LMS Quality (X_2). Meanwhile, the remaining 23.1% is explained by other factors outside this research model, such as students' intrinsic motivation, time availability, or other external factors not examined.

Second, the R-Square value for the Student Achievement variable (Y) of 0.646 indicates that 64.6% of the variation in student academic achievement can be explained by the three independent and mediating variables in this model, namely E-Learning Utilization (X_1), LMS Quality (X_2), and Online Interaction (Z). The remaining 35.4% is influenced by other variables outside the scope of this study, such as independent learning ability, psychological condition, economic background, or the physical learning environment.

Overall, the results of this analysis indicate that the research model has strong explanatory power, with the independent variables contributing significantly to the dependent variable. The high R-square values for both constructs demonstrate that the use of the Moodle LMS at Universitas Terbuka, through the dimensions of system quality and student usage intensity, plays a significant role in increasing online interaction and ultimately impacting student academic achievement in online learning in the even semester of 2024.

Model Goodness Test (Goodness of Fit)

The goodness-of-fit (Q-square) of a PLS model is assessed using the Q-square value, which functions similarly to the coefficient of determination (R-square) in regression analysis. The higher the Q-square value, the better the model fits the data. The following are the results of the Q-square calculation:

Q Square $= 1 – [(1 – R2_1) \times (1 – R2_2)]$
$= 1 – [(1- 0.769) \times (1-0.646))$
$= 1 – (0.231 \times 0.354)$
$= 1 – 0.0811$
$= 0.918$

Based on these calculations, the Q-Square value obtained was 0.918, or 91.8%. This indicates that the research model can explain 91.8% of the diversity in the data studied, while the remaining 8.2% is explained by other factors not included in this study. Thus, the results indicate that this research model has a good level of fit.

Hypothesis Testing

Based on the data analysis conducted, the results can be used to test the research hypothesis by referring to the r statistic and P value. The hypothesis will be accepted if the P value is less than 0.05. This study involves direct and indirect influences, considering there are independent variables, dependent variables, and mediating variables. This study proposes 3 hypotheses, which are tested using bootstrapping analysis techniques. Through the results of the t-statistics obtained, the significance of the influence of the independent variables on the dependent variable can be determined. If the t-statistic value is greater than 1.967 (TINV (0.05,50), which is the t-table value at a significance level of 5%), then the effect is considered significant. In addition, the results of the P value are also analyzed; if the P value for each variable is less than 0.05, then the null hypothesis (H0) will be rejected. A positive influence can be determined through the Original Sample value. The following is a summary of the test results:

Table 2 Results of Direct Influence Testing

Variables	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Information
X1 -> X2	0.914	0.913	0.024	37,829	0,000	Positive and significant
X1 -> Y	-0.019	-0.0 2 5	0.144	0.134	0.893	Negative and insignificant
X1 -> Z	0.478	0.456	0.142	3,356	0.001	Positive and significant
X2 -> Y	0.234	0.248	0.119	1,974	0.049	Positive and significant
X2 -> Z	0.487	0.508	0.134	3,622	0,000	Positive and significant

Z -> Y	0.767	0.757	0.138	5,557	0,000	Positive and significant

Source: Data Processed by Researchers, 2023

Discussion

The Effect of E-Learning Utilization on LMS Quality ($X_1 \rightarrow X_2$)

The path analysis results show that the use of e-learning (X_1) has a very strong, positive, and significant influence on the perception of LMS quality (X_2), with a coefficient of 0.914, a T-statistic of 37.829, and a p-value of 0.000. This means that the more active students are in using an LMS such as Moodle, the higher their positive perception of the platform's quality. This finding is relevant in the context of the Open University, which relies on online learning as its primary method.

Theoretically, this can be explained through the Technology Acceptance Model (TAM) by Davis (1989), which states that perceived ease of use and perceived usefulness are formed from user experience. Venkatesh & Davis (2000) added that repeated involvement in a technology system will form a positive attitude towards the effectiveness and benefits of the system. In this context, students who use an LMS more frequently tend to be more familiar with its features, navigation, and reliability, which ultimately forms a high perception of quality.

Research by Al-Fraihat, Joy, and Sinclair (2020) showed that perceived LMS quality increased with usage intensity, including technical aspects such as responsiveness and features. A similar finding was found by Putra & Wahyuni (2021) at Yogyakarta State University, where active students rated Moodle as more stable and easier to use. A study by Abdullah (2022) at UIN Makassar also showed that 82% of active students accessed the LMS more than five times a week and gave a positive assessment of its quality.

The implication is that improving the perceived quality of an LMS depends not only on technical improvements but also on user engagement. Institutions need to encourage students to actively use LMS features through outreach, training, and interactive instructional design. Park (2009) emphasized that user satisfaction with an LMS is a crucial determinant of system usage and learning outcomes.

Furthermore, positive perceptions of the LMS also increase trust in the online learning system, which is crucial in the context of minimal face-to-face interaction. Statistically, the T-statistic value > 1.96 and p-value < 0.05 indicate a highly significant effect. In conclusion, active student engagement in e-learning drives positive perceptions of LMS quality, which supports the overall effectiveness of online learning.

The Effect of E-Learning Utilization on Student Achievement ($X_1 \rightarrow Y$)

The results of quantitative analysis using SmartPLS show that the use of e-learning (X_1) does not have a direct significant effect on student achievement (Y), with a path coefficient of -0.019, a T-statistic of 0.134, and a p-value of 0.893. This means that the frequency of use of LMS such as Moodle does not necessarily improve student academic achievement at Universitas Terbuka (UT). This challenges the common assumption that the intensity of e-learning access is always directly proportional to learning outcomes.

Sun et al. (2008) emphasized that frequent LMS use is insufficient if it is not accompanied by active engagement in discussions, reflection, or other cognitive activities. UT students generally only use the LMS to access materials and submit assignments, not for active interaction or reflective learning. Jo, Park, & Lee (2017) also stated that meaningful activities such as discussions and responding to lecturers contribute more to achievement than passive activities such as logging in or downloading files.

A small negative coefficient could also indicate digital fatigue or cognitive overload resulting from excessive e-learning use without varied learning strategies. Keller & Cernerud

(2002) stated that heavy reliance on online platforms can decrease motivation and lead to boredom, especially if not balanced with a varied and personalized learning approach.

These findings demonstrate the importance of mediating variables, such as online interaction (Z) and LMS quality (X_2), in bridging the gap between e-learning utilization and achievement. Wang et al. (2013) explained that learning outcomes in a technological context are influenced by technopedagogical and psychosocial factors, not just the frequency of platform use. In this study, the indirect effect through online interaction was significant.

The implication is that UT's e-learning development policy should not only emphasize increasing access but also improving the quality of use. This includes instructional design that encourages discussion, collaboration, and reflection. An activity-centered learning approach should be adopted, as should the development of an LMS analytics dashboard to monitor and track student usage patterns.

Statistically, the high p-value and low T-statistic reject a significant direct relationship. In conclusion, the use of e-learning must be accompanied by active interaction, good platform quality, and pedagogical support to have a positive impact on academic achievement (Sun et al., 2008; Jo et al., 2017; Keller & Cernerud, 2002; Wang et al., 2013).

The Effect of E-Learning Utilization on Online Interactions ($X_1 \rightarrow Z$)

The results of the path analysis show that the use of e-learning (X_1) has a positive and significant effect on online interaction (Z), with a path coefficient of 0.478, a T-statistic of 3.356, and a p-value of 0.001. This means that the more active students are in using LMS such as Moodle, the higher their involvement in digital interactions, both with lecturers and fellow students.

These findings confirm that e-learning is not only a means of accessing materials but also facilitates two-way communication and collaborative learning. Students who actively participate in discussion forums, synchronous video sessions, and commenting features demonstrate higher levels of online interaction. This aligns with Moore's (1989) Three Types of Interaction theory , which states that learning interactions consist of student-content, student-instructor, and student-student interactions. Intensive use of e-learning allows for all three types of interactions to occur.

The Community of Inquiry model (Garrison, Anderson, & Archer, 2000) supports this by emphasizing the importance of cognitive presence , social presence , and teaching presence . An LMS like Moodle can facilitate social presence through discussion forums that encourage mutual trust and collaboration among learners. Hrastinski (2009) also emphasized that synchronous activities such as webinars can increase emotional engagement, while asynchronous activities support in-depth reflection in online interactions.

In the context of the Open University (UTO), e-learning is the backbone of learning. Students who frequently access the LMS, access materials, or upload assignments are more likely to engage in digital conversations and academic discussions. Therefore, lecturers need to design learning activities that not only present content but also encourage active participation through open-ended questions, peer review, and collaborative forums.

Moodle features like interactive quizzes, chat rooms, and integration with Zoom also enhance online interaction. However, meaningful interactions don't happen automatically; they are influenced by students' intrinsic motivation, technological support, and appropriate instructional design.

Theoretically, this relationship is supported by the Theory of Planned Behavior (Ajzen, 1991), which explains that the intensity of technology use, such as an LMS, is influenced by behavioral intentions stemming from positive attitudes and social norms. In conclusion, active e-learning utilization can improve the quality of online interactions, which plays a crucial role in the success of online learning in higher education.

The Effect of LMS Quality on Student Achievement ($X_2 \rightarrow Y$)

The analysis results show that the quality of the Learning Management System (LMS) has a positive and significant influence on student achievement, with a path coefficient of 0.234, a T-statistic of 1.974, and a p-value of 0.049. This means that the higher students' perceptions of LMS quality related to navigation, access speed, ease of use, system stability, and completeness of features the greater the likelihood of them achieving good academic results, such as a high GPA or achieving Graduate Learning Outcomes (CPL).

Theoretically, a quality LMS is a crucial component in online learning because it serves as the primary link between students, learning materials, and lecturers. A fast, stable, and easy-to-use LMS increases motivation, learning efficiency, and material comprehension. Conversely, a slow or confusing system can decrease engagement and negatively impact academic achievement (Al-Fraihat et al., 2020).

Sun et al. (2008) stated that user satisfaction with e-learning is strongly influenced by interface design, system speed, and support for active learning features. This satisfaction is an important mediator between LMS quality and academic outcomes. In practice, a reliable LMS allows students to access materials, forums, and assignments without technical barriers, supporting the formation of structured learning patterns.

A study by Muslimin & Widodo (2021) at UIN Makassar corroborates these findings, showing that Moodle quality significantly impacts academic achievement, with an R^2 value of 0.606. In the context of Universitas Terbuka (Open University), students' positive perceptions of Moodle also contribute to academic achievement, particularly in the Faculty of Economics.

DeLone & McLean IS Success Model (2003) explains that system quality and information quality influence user satisfaction, which impacts net benefits , including academic outcomes. Meanwhile, the Technology Acceptance Model (Davis, 1989) states that Perceived Ease of Use and Perceived Usefulness determine technology acceptance and user satisfaction.

Zhou (2016) added that LMS user satisfaction is directly related to emotional engagement and learning outcomes . Therefore, it is crucial for institutions to continuously develop their LMS through interface improvements, collaborative features, technical support, and training for both lecturers and students. In conclusion, a high-quality LMS is a crucial foundation for supporting student academic achievement in online learning environments.

The Effect of LMS Quality on Online Interaction ($X_2 \rightarrow Z$)

The analysis results show that the quality of the Learning Management System (LMS) has a positive and significant influence on students' online interactions, with a path coefficient of 0.487, a T-statistic of 3.622, and a p-value of 0.000. This indicates that the higher students' perceptions of LMS quality including ease of navigation, access speed, system stability, and completeness of features the higher the intensity of their interactions in discussion forums, synchronous sessions, and communication with lecturers and colleagues.

These findings align with User Engagement theory , which states that well-designed digital systems can encourage cognitive and emotional user engagement (O'Brien & Toms, 2008). An intuitive and stable LMS makes students more comfortable asking questions, discussing, and participating in online classes (Martin et al., 2020). Conversely, a poorly designed LMS hinders interaction and decreases learning motivation.

According to the DeLone & McLean IS Success Model (2003), system and information quality drives satisfaction and usage intentions, which ultimately impact net benefits, including online learning interactions. Research by Al-Fraihat et al. (2020) reinforces this by showing that LMS quality significantly impacts student engagement , particularly if the LMS provides interactive features such as forums and collaborative sessions.

Muslimin & Widodo (2021) also showed that high perceptions of the quality of the Moodle LMS at UIN Makassar correlated with increased student participation in discussion forums and synchronous classes. This suggests that a well-designed LMS fosters effective two-way communication. Furthermore, quality interactions foster a sense of ownership in the learning process, strengthening student emotional engagement (Garrison, Anderson & Archer, 2000).

Features such as automatic notifications, assignment comments, and internal messaging also allow lecturers to provide quick and personalized feedback, which is essential for maintaining ongoing discussions (Borup et al., 2014). In the context of the Open University using Moodle, feature enhancements and lecturer training are crucial for the continued growth of online interactions.

Finally, Zhou (2016) emphasized the importance of supporting multimodal interactions (text, voice, video) to strengthen student engagement across various learning styles. In conclusion, a high-quality LMS is a crucial foundation for building intensive, meaningful online interactions and supporting the long-term success of online learning.

The Effect of Online Interaction on Student Achievement (Z → Y)

The results of the study indicate that online interaction (Z) has a positive and significant influence on student academic achievement (Y), with a path coefficient of 0.767, a T-statistic of 5.557, and a p-value of 0.000. This indicates that the intensity of student interaction whether through discussion forums, synchronous classes (Zoom), or communication with lecturers is strongly correlated with improved learning outcomes. This finding aligns with Vygotsky's (1978) theory of Social Constructivism , which states that learning is a social activity that relies on interactions between individuals. In the context of online learning, these interactions are mediated by technology through the LMS as the primary platform for collaboration and exchange of ideas (Moore, 1989).

According to the Community of Inquiry Framework (Garrison et al., 2000), effective learning is created through teaching presence , social presence , and cognitive presence , all of which are strengthened through online interactions. Research by Borup et al. (2014) confirms that the quality and frequency of online communication positively impact motivation and academic outcomes. Similarly, Dennen (2008) showed that active participation in online discussion forums correlates with high academic performance and the development of critical thinking skills.

At Universitas Terbuka (Open University), the LMS Moodle provides features such as forums, comments, quizzes, and video conferencing, facilitating effective academic interaction. The presence of lecturers in synchronous classes also plays a crucial role in guiding discussions, motivating students, and providing feedback (Martin et al., 2020). Effective interactions help build a learning community that enhances students' sense of engagement with the academic environment, which is crucial in the context of UT, where students are geographically dispersed (Rovai, 2002).

Statistically, the coefficient of 0.767 indicates that online interaction explains more than 76% of the influence on academic achievement, supported by an R^2 value of 0.646. Ghazal et al.'s (2018) research also emphasized that the frequency of discussion participation and synchronous attendance are closely related to academic achievement. However, the quality of interaction—in terms of the depth and meaningfulness of discussions is more important than frequency alone (Sher, 2009).

Overall, online interaction proved to be a key mediating variable in the relationship between e-learning utilization, LMS quality, and student achievement. Therefore, strengthening digital interaction needs to be a priority in strategies to improve the quality of online learning.

CONCLUSION

Based on the results of path analysis and theoretical studies, this study produced six main findings that are interrelated in explaining the dynamics of e-learning utilization, LMS quality, online interactions, and academic achievement of Open University students.

This study yielded six key findings related to e-learning utilization and its impact on LMS quality, online interaction, and student academic achievement. First, e-learning utilization was shown to have a very strong and significant influence on perceived LMS quality (coefficient 0.914; p-value 0.000), in line with the Technology Acceptance Model. Second, e-learning utilization had no direct effect on academic achievement (coefficient –0.019; p-value 0.893), indicating that frequent use without active engagement was not sufficient to improve academic achievement.Third, e- learning had a significant positive impact on student online interaction (coefficient 0.478; p-value 0.001), reinforcing the importance of interaction in online learning according to Moore's theory and the Community of Inquiry model. Fourth, LMS quality significantly influenced online interaction (coefficient 0.487; p-value 0.000), emphasizing the role of system convenience in enhancing user engagement. Fifth, LMS quality also significantly impacts student academic achievement (coefficient 0.234; p-value 0.049), consistent with DeLone & McLean's information systems success model. Sixth, online interaction demonstrates the strongest influence on academic achievement (coefficient 0.767; p-value 0.000), underscoring the importance of social presence and active engagement in digital learning.

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