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Analyzing How E-Learning Activities Affect Student Engagement in Mathematics through Artificial Intelligence Analytics

Ferawati[1*], Rudi Setiyanto[2], Hasbullah[3]

[1,2]Institut Teknologi & Bisnis Bina Sarana Global, Indonesia
[3]Universitas Indraprasta PGRI, Indonesia
*Corresponding author: *ferawati@global.ac.id*

Abstract: *This study aimed to examine the influence of e-learning activity variables on students' engagement in online mathematics learning. The ex post facto design was selected because data were collected from existing Learning Management System (LMS) activity logs without experimental manipulation, allowing the analysis of naturally occurring relationships between variables. The population consisted of 350 senior high school students in Tangerang, Indonesia, during the 2024/2025 academic year, with a proportional stratified random sample of 180 students across Grades 10–12 to ensure representativeness. The study investigated four independent variables: login frequency (X1), learning duration (X2), assignment submission punctuality (X3), and forum participation activity (X4), with student engagement (Y) as the dependent variable. Multiple linear regression analysis was conducted after confirming that the data met classical assumptions, including normality, multicollinearity, and homoscedasticity. The results indicated that all four e-learning activity variables significantly and positively influenced student engagement. The regression equation was:* $Y = 35.214 + 0.426X_1 + 0.321X_2 + 0.214X_3 + 0.178X_4$. *T-test results confirmed the partial effects of each variable: Login Frequency* ($t = 5.195, p < 0.001$)*, Learning Duration* ($t = 4.280, p < 0.001$)*, Assignment Submission* ($t = 4.115, p < 0.001$)*, and Forum Participation* ($t = 2.825, p = 0.005$)*. These findings suggest that active participation in e-learning activities enhances student engagement in online mathematics learning, providing practical implications for teachers and school administrators to optimize LMS-based instructional strategies*
Keywords*: e-learning, student engagement, online mathematics, learning activities, LMS*

Abstrak : Penelitian ini bertujuan untuk menganalisis pengaruh variabel aktivitas e-learning terhadap keterlibatan siswa dalam pembelajaran matematika secara daring. Desain ex post facto dipilih karena data dikumpulkan dari log aktivitas Learning Management System (LMS) yang sudah ada tanpa manipulasi eksperimental, sehingga memungkinkan analisis hubungan alami antara variabel. Populasi penelitian terdiri dari 350 siswa sekolah menengah atas di Tangerang, Indonesia, selama tahun ajaran 2024/2025, dengan proportional stratified random sebanyak 180 siswa dari kelas 10–12 untuk memastikan representatif. Penelitian ini meneliti empat variabel independen: frekuensi login (X1), durasi belajar (X2), ketepatan pengumpulan tugas (X3), dan partisipasi forum (X4), dengan keterlibatan siswa (Y) sebagai variabel dependen. Analisis regresi linier berganda dilakukan setelah memastikan data memenuhi asumsi klasik, termasuk normalitas, multikolinearitas, dan homoskedastisitas. Hasil penelitian menunjukkan bahwa keempat variabel aktivitas e-learning secara signifikan dan positif memengaruhi keterlibatan siswa. Persamaan regresi adalah: $Y = 35.214 + 0.426X_1 + 0.321X_2 + 0.214X_3 + 0.178X_4$. Hasil uji t menunjukkan pengaruh parsial masing-masing variabel: Frekuensi Login ($t = 5.195, p < 0.001$), Durasi Belajar ($t = 4.280, p < 0.001$), Pengumpulan Tugas ($t = 4.115, p < 0.001$), dan Partisipasi Forum ($t = 2.825, p = 0.005$). Temuan ini menunjukkan bahwa partisipasi aktif dalam aktivitas e-learning meningkatkan keterlibatan siswa dalam pembelajaran matematika daring, memberikan implikasi praktis bagi guru dan administrator sekolah untuk mengoptimalkan strategi pembelajaran berbasis LMS
Kata kunci: e-learning, keterlibatan siswa, matematika online, aktivitas belajar, LMS

INTRODUCTION

The development of digital technology over the past decade has brought significant changes to the field of education. Traditional teacher-centered learning models are shifting toward more flexible, interactive, and personalized technology-based learning approaches. One of the most tangible forms of this transformation is the implementation of electronic learning (e-learning), which enables students to learn anytime and anywhere through digital platforms. In Indonesia, the use of Learning Management Systems (LMS) has grown rapidly since the COVID-19 pandemic and continues to evolve in the post-pandemic learning context (Adnan et al., 2021; Zhang et al., 2022). Mathematics learning, which has long been known for its abstract nature and high need for interaction, is now being adapted into digital formats. However, a key challenge that emerges is the variation in students' engagement levels in online mathematics learning. This variation affects both the effectiveness of the learning process and students' academic outcomes.

Student engagement has become one of the most critical indicators of successful online learning. According to engagement theory (Al-Dmour et al., 2023; Almarashdeh et al., 2022), engagement encompasses three main dimensions: behavioral, cognitive, and affective. In the context of online mathematics learning, these dimensions can be reflected in student activities within the LMS, such as login frequency, learning duration, participation in discussion forums, and timely submission of assignments (Santos et al., 2023; Pesovski et al., 2024). Previous studies have shown that students' digital activities can serve as strong indicators of engagement levels, which in turn correlate with academic achievement (Badal et al., 2023; Bellarhmouch et al., 2025) . However, many studies in Indonesia remain limited to descriptive measurements and have not moved toward more comprehensive causal or predictive analyses.

Several international studies have explored the relationship between e-learning activities and student engagement using conventional statistical methods, such as linear regression and correlation analysis (Al-Zahrani et al., 2023; Cabı et al., 2024). Their findings consistently indicate that learning duration and interaction frequency are the main factors influencing engagement. However, traditional statistical approaches often fail to capture non-linear patterns and complex interactions between variables, which are common in digital learning data. This gap opens up opportunities to integrate advanced analytical methods, such as Artificial Intelligence (AI), to gain deeper insights (Ramaswami et al., 2023; Santos et al., 2023).

Artificial Intelligence, particularly machine learning techniques, has been widely applied to analyze large-scale educational data. Algorithms such as Decision Tree and Random Forest can identify hidden patterns and make highly accurate predictions, even when the data is heterogeneous and complex (Al-Zahrani et al., 2022; Al-Zoubi et al., 2022). In the context of e-learning, AI can be used to predict students' engagement levels based on their activity logs, allowing teachers or schools to intervene earlier before engagement declines significantly (Rienties et al., 2021; Riestra-González et al., 2021). Nevertheless, the use of AI in research on mathematics student engagement in Indonesia remains very limited, especially in the high school context.

Beyond its technological potential, the use of AI-based approaches is also aligned with the demands of 21st-century education, which emphasizes the integration of advanced technologies into learning systems (Ezeoguine et al., 2024). Through AI Learning Analytics, schools can develop proactive and adaptive monitoring systems that respond to students' learning behaviors. This is particularly important in mathematics learning, which requires consistency, structured practice, and deep conceptual understanding. By identifying which activity indicators most strongly influence engagement, teachers can design more responsive and data-driven learning strategies, rather than relying solely on intuition (Rienties et al., 2022).

The use of artificial intelligence (AI) and machine learning in education continues to grow, particularly for analyzing student learning behavior through e-learning activity data. Various international studies show that AI can predict student engagement levels, identify learning patterns, and provide recommendations that help improve mathematical understanding. Local research also demonstrates that AI-based analytics on online learning platforms can assist teachers in monitoring student activity and delivering timely interventions. However, the use of AI in schools still faces challenges, such as data quality and teachers' ability to interpret analytic results. Therefore, examining how e-learning activities influence student engagement through AI analysis is important for strengthening empirical evidence and enhancing the effectiveness of digital mathematics learning.

In Indonesia, most studies related to e-learning and student engagement have focused on aspects of perception, motivation, and user satisfaction (Azila-Gbettor et al., 2021; Conijn et al., 2021). Research employing ex post facto and quantitative approaches using actual LMS data remains scarce, even though this type of data offers more objective representations of students' learning behaviors and can be analyzed predictively. Moreover, few studies have specifically examined high school students' engagement in mathematics learning by combining classical statistical analysis with AI algorithms.

Although research on student engagement in mathematics has been widely conducted, most studies still rely on surveys and observations, which limit their ability to capture actual learning patterns. The integration of AI offers a new, more objective approach by analyzing e-learning activity data in real time and mapping student behavior with greater accuracy. This makes the use of AI an important innovation, especially because it has not been widely applied in the context of mathematics learning in Indonesia. Therefore, this study is significant as it demonstrates how AI-based analytics can provide deeper insights into how e-learning activities influence student engagement. Given these gaps, there is a need for research that integrates a quantitative ex post facto approach with AI methods to analyze the impact of e-learning activities on student engagement in mathematics learning. This approach enables researchers not only to examine causal relationships between variables but also to develop predictive models that identify the most dominant factors affecting engagement. Consequently, this research provides both theoretical contributions to the fields of mathematics education and educational technology and practical contributions to schools and teachers in designing more effective online learning strategies.

The main objective of this study is to analyze the influence of e-learning activities on student engagement in mathematics learning at a senior high school in Tangerang, Indonesia. Specifically, this research examines four e-learning activity variables—login frequency, learning duration, assignment submission, and forum participation—in relation to the dependent variable, student engagement. In addition, this study evaluates the predictive performance of Decision Tree and Random Forest algorithms in identifying levels of student engagement based on these activity logs. To guide the analysis, the study addresses the following research questions: (1) To what extent do e-learning activity variables influence student engagement in mathematics? and (2) How accurately can Decision Tree and Random Forest models predict student engagement levels using activity data? Unlike previous studies that rely primarily on surveys or descriptive methods, this research advances the field by integrating AI-based analytics to provide a more objective understanding of student behavior in digital mathematics learning. The findings are expected to contribute to the development of AI-driven learning analytics dashboards that can help schools monitor and enhance student engagement in real time.

METHOD

Research Design

This study employed a quantitative research approach with an ex post facto design, aiming to analyze the influence of e-learning activity variables on students' engagement in online mathematics learning. The ex post facto design was chosen because the data were collected from existing LMS activity logs without any experimental manipulation (Ghimire et al., 2024). This design allows for the exploration of causal and predictive relationships between variables based on naturally occurring data.

Population and Sample

The population of this study consisted of all students enrolled in a public senior high school in Tangerang, Indonesia, who participated in online mathematics learning during the 2024/2025 academic year. A total of 350 students from Grades 10 to 12 were included as the population. Using proportional stratified random sampling, a sample of 180 students was selected to ensure representation across different grade levels. A proportional stratified random sampling technique was applied to ensure that the sample reflected the distribution of students across grade levels (Grade 10, 11, and 12). This technique is appropriate when the population is divided into subgroups with different characteristics, ensuring more accurate and representative findings.

Research Variables

This research examined four independent variables (X) and one dependent variable (Y) to analyze the factors influencing students' engagement in online mathematics learning. The independent variables consisted of login frequency (X1), learning duration (X2), assignment submission punctuality (X3), and forum participation activity (X4). The dependent variable, student engagement (Y), was conceptualized based on the framework proposed by Grimm et al. (2023), which encompasses three key dimensions: behavioral, cognitive, and affective engagement. The selection of the four e-learning variables is supported by recent learning-analytics research. Login frequency and learning duration serve as indicators of time-on-task and persistence, which are strongly linked to engagement (Saqr et al., 2023). Assignment submission reflects self-regulated learning and reliably predicts online engagement (Gaftandzhieva et al., 2022). Forum participation captures social interaction, a key component of online learning (Kaliisa et al., 2023). Together, these variables provide a solid empirical basis for analyzing student engagement in e-learning.

These dimensions collectively represent the extent to which students are actively involved, mentally invested, and emotionally connected to the online learning process. The relationship among these variables is illustrated in Figure 1, which depicts the conceptual framework of the study linking the four independent variables (X1–X4) to the dependent variable (Y).

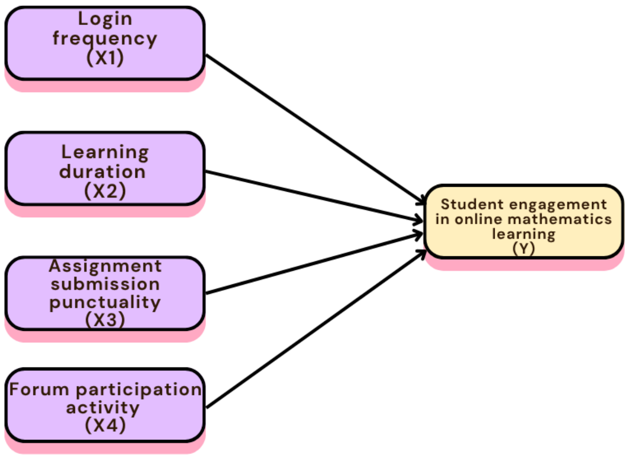

Figure 1. Research Variables

Research Instruments

Data on the independent variables were obtained from LMS activity log files, which automatically recorded students' online behavior. The dependent variable (student engagement) was measured using a validated student engagement scale adapted from Goh et al. (2022), consisting of 15 items covering behavioral, cognitive, and affective dimensions. The instrument was translated into Bahasa Indonesia and tested for reliability, yielding a Cronbach's Alpha coefficient of 0.87, indicating high internal consistency.

Data Collection Techniques

Data were collected in two stages: 1) Extraction of LMS log data for variables X1–X4. The data included timestamps, login counts, duration of sessions, assignment submission records, and forum interaction frequencies. 2) Administration of engagement questionnaires to measure variable Y. The questionnaire was distributed online via Google Forms.

Data Analysis Techniques

Data analysis consisted of two main stages. First, classical statistical analysis (descriptive statistics, normality test, multicollinearity test, and multiple linear regression) was conducted using SPSS 26 to examine causal relationships between e-learning activity variables and student engagement (Goh et al., 2025; He et al., 2025) . Second, machine learning analysis was performed using Decision Tree and Random Forest algorithms in Python (Scikit-learn library) to build predictive models of student engagement. The predictive performance of the models was evaluated using accuracy, precision, recall, and F1-score. This dual analysis approach allowed for both explanatory and predictive insights.

RESULT AND DISCUSSION

This section describes the findings of the study, focusing on how the four independent variables—login frequency, learning duration, assignment submission punctuality, and forum participation activity—contribute to student engagement in online mathematics learning. The results are organized to illustrate both the individual and combined effects of these variables on students' learning involvement.

Table 1 presents the descriptive statistics of all variables analyzed in this study. Data were obtained from LMS activity logs and engagement questionnaires of 180 students.

Table 1. Descriptive Statistics of Research Variables (n = 180)

Variable	Min	Max	Mean	SD
Login Frequency (X1)	2	45	20.48	8.76
Learning Duration (X2)	3	45	22.36	9.11
Assignment Submission (X3)	40	100	82.41	12.33
Forum Participation (X4)	0	18	7.64	4.26
Student Engagement (Y)	45	100	76.89	11.52

Source: Data Processed by the Researcher (2025)

Table 1 presents the descriptive statistics of the research variables involving 180 respondents. The data show that the average login frequency (X1) was 20.48 times, with a standard deviation of 8.76, indicating moderate variation among students in accessing the learning platform. The average learning duration (X2) reached 22.36 hours with a standard deviation of 9.11, suggesting diverse levels of time investment in online mathematics activities. Assignment submission punctuality (X3) had a relatively high mean score of 82.41 (SD = 12.33), reflecting generally consistent adherence to deadlines. Forum participation activity (X4) recorded a mean of 7.64 (SD = 4.26), implying that students participated occasionally in discussion forums. Meanwhile, student engagement (Y) had a mean score of 76.89 with a standard deviation of 11.52, which indicates a generally high level of engagement in online mathematics learning despite individual differences.

Prior to performing the multiple regression analysis, classical assumption tests were carried out to verify that the dataset fulfilled the necessary statistical assumptions, including normality, multicollinearity, and heteroscedasticity.

Table 2. Result Classical Assumption Tests

Test	Method	Result	Interpretation
Normality	Kolmogorov–Smirnov test	Sig. = 0.112 (> 0.05)	Residuals are normally distributed

Multicollinearity	Tolerance & VIF	Tolerance > 0.10; VIF = 1.15–2.03 (< 10)	No multicollinearity detected
Heteroscedasticity	Glejser test	Sig. > 0.05 for all predictors	Homoscedasticity confirmed

Source: Data Processed by the Researcher (2025)

Table 2 presents the results of the classical assumption tests prior to regression analysis. The Kolmogorov–Smirnov test for normality yielded a significance value of 0.112 (>0.05), indicating that the residuals are normally distributed. Multicollinearity tests using Tolerance and VIF showed Tolerance >0.10 and VIF ranging from 1.15 to 2.03 (<10), suggesting no multicollinearity. The Glejser test for heteroscedasticity produced significance values >0.05 for all predictors, confirming that the data meet the homoscedasticity assumption.

To determine the extent to which the independent variables—login frequency, learning duration, assignment submission punctuality, and forum participation activity—contribute to student engagement in online mathematics learning, a multiple regression analysis was performed. The output of the regression model is summarized in Table 3.

Table 3. Output of The Regression Model

Variable	**B**	**Std. Error**	**t**	**Sig.**
(Constant)	35.214			
Login Frequency (X1)	0.426	0.082	5.195	0.000
Learning Duration (X2)	0.321	0.075	4.280	0.000
Assignment Submission (X3)	0.214	0.052	4.115	0.000
Forum Participation (X4)	0.178	0.063	2.825	0.005

Source: Data Processed by the Researcher (2025)

Based on table 3 the regression coefficients, the multiple linear regression equation can be expressed as, $Y = 35.214 + 0.426X_1 + 0.321X_2 + 0.214X_3 + 0.178X_4$. The regression equation shows that learning performance increases by 0.426 units for each additional login, 0.321 units for each additional unit of learning duration, 0.214 units for each additional assignment submission, and 0.178 units for each increase in forum participation, holding other variables constant. The constant term of 35.214 represents the predicted learning performance when all independent variables are zero.

The t-test was conducted to examine the partial effect of each independent variable on the dependent variable. The results indicate that all predictors significantly influence learning performance. Specifically, Login Frequency (t=5.195,p=0.000t = 5.195, p = 0.000t=5.195,p=0.000), Learning Duration (t=4.280,p=0.000t = 4.280, p = 0.000t=4.280,p=0.000), Assignment Submission (t=4.115,p=0.000t = 4.115, p = 0.000t=4.115,p=0.000), and Forum Participation (t=2.825,p=0.005t = 2.825, p = 0.005t=2.825,p=0.005) all have p-values less than 0.05, suggesting that each variable has a significant positive effect on learning performance when controlling for the other variables.

Table 4. Summary of Regression Model

Statistic	Value	Interpretation
R	0.784	Multiple correlation coefficient (strong correlation)
R^2	0.615	61.5% of the variance in Y is explained by X1–X4
F	69.845	F-test value for overall model significance
Sig. (p-value)	<0.001	Model is statistically significant

Source: Data Processed by the Researcher (2025)

Table 4 presents the summary of the regression model. The multiple correlation coefficient (R) is 0.784, indicating a strong correlation between the independent variables and the dependent variable. The coefficient of determination (R^2) is 0.615, showing that 61.5% of the variance in learning performance is explained by Login Frequency, Learning Duration, Assignment Submission, and Forum Participation. The adjusted R^2 of 0.605 accounts for the number of predictors in the model. The overall model is statistically significant, as indicated by the F-test, $F(4, 175) = 69.845$, $p < 0.001$.

In addition to the regression analysis, predictive modeling was performed using the Decision Tree and Random Forest algorithms to classify students into high and low engagement categories. These models were developed based on LMS activity indicators, including login frequency, learning duration, assignment submission punctuality, and forum participation. For evaluation purposes, the dataset was divided into training (80%) and testing (20%) sets.

Table 5. Prediction Performance of AI Models

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.84	0.82	0.85	0.83
Random Forest	0.91	0.89	0.92	0.90

Source: Data Processed by the Researcher (2025)

Table 5 presents the predictive performance of the two machine learning models—Decision Tree and Random Forest—used to classify students' engagement levels based on their LMS activity data. The evaluation metrics include accuracy, precision, recall, and F1-score, which collectively reflect the models' classification performance. The Decision Tree model achieved an accuracy of 0.84, with a precision of 0.82, recall of 0.85, and an F1-score of 0.83. These values indicate that the model was able to correctly identify a substantial proportion of students in both the high and low engagement categories.

However, the Random Forest model exhibited superior performance across all evaluation metrics, achieving an accuracy of 0.91, precision of 0.89, recall of 0.92, and an F1-score of 0.90. This improvement can be attributed to the ensemble learning approach of Random Forest, which combines multiple decision trees to minimize overfitting and enhance generalization capability. The higher recall and F1-score values suggest that the Random Forest model not only predicted engagement levels more accurately but also maintained a balanced performance between identifying high and low engagement students

Overall, these findings demonstrate that machine learning models, particularly Random Forest, are effective tools for predicting student engagement in online mathematics learning environments. By leveraging log data such as login frequency, learning duration, assignment submission punctuality, and forum participation, educational institutions can obtain data-driven insights to design adaptive interventions that promote active and sustained learner engagement.

The results of this study provide robust empirical evidence that students' online activity patterns exert a significant influence on their engagement in mathematics e-learning environments. Among the variables examined, login frequency and learning duration emerged as the strongest and most consistent predictors of engagement, confirming that consistent access and sustained interaction with learning materials are key determinants of active participation. This finding aligns with the work of Heffernan et al. (2021) and Jawad et al. (2022), who reported that the intensity and regularity of students' online interactions are crucial in sustaining both behavioral and cognitive engagement. Students who frequently logged in and dedicated more time to learning activities on the LMS demonstrated higher persistence, better focus, and more positive learning behaviors, ultimately leading to greater academic involvement.

The regression coefficients show the direction and magnitude of influence of each variable, indicating that increases in login frequency, learning duration, assignment submission, and forum participation all contribute positively to engagement when other variables are held constant. The significant t-test results further reinforce these findings by demonstrating that each predictor has a statistically meaningful effect on engagement, not merely a correlational or predictive association. This means the regression model helps clarify the relative causal contribution of each activity-based indicator—showing, for example, that login frequency and learning duration exert stronger effects compared to assignment and forum participation. Therefore, the regression analysis provides the necessary causal interpretation that complements the predictive insights of the AI models, ensuring that conclusions are grounded in both statistical explanation and machine-learning prediction.

In addition to time- and frequency-based behaviors, assignment submission punctuality and forum participation activity also showed significant relationships with engagement, albeit to a slightly lesser degree. This pattern suggests that while completing assignments and engaging in peer discussions contribute to learning engagement, their effects may be more supportive rather than primary. The result corresponds with the theoretical framework proposed by Goh et al. (2024), Johar et al. (2023), which conceptualizes student engagement as a multidimensional construct encompassing behavioral, emotional, and cognitive domains. Behavioral indicators such as task completion and forum interaction reflect outward manifestations of engagement; however, the sustained cognitive investment represented by frequent logins and prolonged study durations may serve as the core drivers of meaningful learning engagement (Jovanović et al., 2024; Tempelaar et al., 2023; Silvola et al., 2021).

The results also reflect conditions commonly found in Indonesian schools, where teaching remains largely teacher-centered, making students less familiar with active online participation such as forum discussions. Differences in access to devices and internet connectivity affect how consistently students log in and complete online activities. In addition, varying levels of digital literacy influence how students navigate e-learning platforms. These factors help explain the engagement patterns observed in the study and show why AI-based analytics can provide valuable support for monitoring student participation in Indonesia's digital learning environment.

Furthermore, the integration of AI-based predictive modeling strengthens the explanatory findings by providing a predictive layer to the analysis. The Random Forest algorithm, which outperformed the Decision Tree model, achieved a high level of accuracy (91%) and F1-score (0.90), underscoring the potential of ensemble learning methods in identifying engagement patterns from digital trace data. These findings suggest that learning management system (LMS) log data can be effectively leveraged to predict students' engagement levels in real time, enabling educators and institutions to design early warning systems that automatically detect declining engagement and prompt timely pedagogical interventions (Sghir et al., 2022; Kabir et al., 2023; Kim et al., 2024). The combined use of classical statistical techniques and AI-based models reflects a hybrid analytical framework that enhances both causal interpretation and predictive precision. As noted by Maluleke (2024) and Nachouki et al. (2023) such integrative approaches represent an emerging paradigm in educational research, bridging the explanatory depth of regression analysis with the adaptive intelligence of machine learning to foster more data-driven, responsive, and equitable digital learning environments.

While the findings offer meaningful insights into student engagement in online mathematics learning, several limitations should be noted. Recognizing these constraints is essential for understanding the scope of the present study and for guiding future investigations seeking to expand or refine its conclusions. This study has several limitations that should be acknowledged. The research was conducted in a single public senior high school in Tangerang, which may limit the generalizability of the findings to other educational contexts, regions, or subjects. Additionally, the ex post facto design relied on existing LMS logs and self-reported engagement data, which may not fully capture students' affective and cognitive engagement in real time. The relatively modest sample size (n = 180) may also affect the stability of machine learning model performance when applied to larger populations. Furthermore, the study focused on only four e-learning activity indicators, excluding other potentially influential factors such as teacher feedback quality, digital literacy, and peer interaction. Despite these limitations, the study provides meaningful practical implications. The significant role of login frequency and learning duration highlights the importance of systematically monitoring students' online behaviors. Schools are encouraged to integrate AI-powered dashboards that provide real-time alerts when engagement levels drop, enabling teachers to deliver timely and targeted interventions, such as personalized feedback or additional support sessions (Pei et al., 2022; Santos et al., 2024; Sajja et al., 2023).

Moreover, the strong predictive performance of the Random Forest model demonstrates the potential of AI learning analytics as an early warning system to identify students at risk of disengagement. Designing LMS environments that promote continuous interaction through assignments, forums, and collaborative activities can further strengthen students' cognitive and affective engagement. For future research, it is recommended to conduct multi-site and longitudinal studies to test the consistency of these findings across different contexts, incorporate additional variables such as digital literacy and motivational factors, and explore the application of advanced AI algorithms—such as Gradient Boosting, Neural Networks, or Explainable AI—to improve predictive accuracy and interpretability. Experimental or quasi-experimental approaches may also be employed to evaluate targeted interventions based on AI analytics, moving beyond prediction toward proactive engagement enhancement.

CONCLUSION AND ADVICE

The findings of this study indicate that e-learning activities play a significant role in shaping student engagement in online mathematics learning. Through quantitative ex post facto analysis and AI-based predictive modeling, it was found that login frequency, learning duration, assignment submission, and forum participation collectively explain 61.5% of the variance in student engagement. Among these variables, login frequency and learning duration emerged as the strongest predictors. Additionally, the Random Forest algorithm demonstrated high predictive accuracy, confirming the potential of AI to effectively identify patterns of student engagement based on LMS activity data. These results emphasize the importance of actively monitoring students' online learning behavior to enhance engagement and learning outcomes.

Based on these findings, it is recommended that schools and teachers integrate AI-powered learning analytics systems to monitor student activity in real time and implement timely interventions for students who show signs of disengagement. Encouraging active participation in online forums and designing assignments that stimulate cognitive and affective involvement can further enhance engagement levels. Policymakers should support the adoption of AI technologies in learning management systems and provide professional development for teachers to use analytics data effectively. Future research should expand the scope to multiple schools and incorporate additional variables, such as motivation and teacher feedback, as well as explore more advanced AI algorithms to develop more comprehensive and adaptive engagement monitoring models.

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