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A QUANTITATIVE STUDY ON AI-SUPPORTED TEACHING AND SELF-REGULATED LEARNING AND THEIR IMPACT ON STUDENT ENGAGEMENT IN HIGHER EDUCATION

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ABSTRAK

Perkembangan teknologi digital dan kecerdasan buatan, yang disertai dengan kemampuan mahasiswa dalam mengatur pembelajarannya secara mandiri, menempatkan pemanfaatan AI dan pembelajaran mandiri sebagai elemen kunci dalam meningkatkan keterlibatan akademik di pendidikan tinggi. Penelitian kuantitatif ini mengkaji pengaruh pembelajaran berbantuan AI dan self-regulated learning (SRL) terhadap keterlibatan mahasiswa di perguruan tinggi Buddhis. Penelitian ini dilaksanakan di perguruan tinggi yang berada di Bandar Lampung dengan mahasiswa Buddhis sebagai unit analisis. Populasi penelitian berjumlah 300 mahasiswa, dengan sampel sebanyak 171 responden. Data dikumpulkan melalui kuesioner skala Likert lima poin dan dianalisis menggunakan teknik regresi linier berganda. Hasil penelitian menunjukkan bahwa pembelajaran berbantuan AI memiliki pengaruh positif dan signifikan terhadap keterlibatan mahasiswa. Demikian pula, self-regulated learning juga terbukti berpengaruh positif dan signifikan terhadap keterlibatan mahasiswa. Temuan ini menegaskan pentingnya pemanfaatan teknologi AI dalam proses pembelajaran serta penguatan kemandirian belajar mahasiswa sebagai strategi untuk mendorong keterlibatan yang lebih mendalam. Secara teoretis, penelitian ini berkontribusi pada pengembangan kajian mengenai pedagogi berbasis AI dan otonomi pembelajar dalam konteks pendidikan tinggi. Secara praktis, penelitian ini memberikan acuan bagi pendidik dan institusi pendidikan dalam merancang model pembelajaran yang mensinergikan dukungan teknologi dengan self-regulated learning guna meningkatkan kualitas keterlibatan mahasiswa dan capaian akademik di era digital.
Kata Kunci: *Pengajaran yang Didukung AI, Otonomi Pembelajaran, Keterlibatan Siswa, Kecerdasan Buatan, Studi Kuantitatif*

ABSTRACT

The advancement of digital technology and artificial intelligence, along with students' capacity for self-regulated learning, positions the use of AI and self-directed learning as key elements in promoting academic engagement in higher education. This quantitative research examines how AI-assisted instruction and self-regulated learning (SRL) influence student engagement within Buddhist higher education institutions. The research was conducted at higher education institutions in Bandar Lampung with Buddhist students as the unit of analysis. The study involved a population of 300 students, from which 171 participants were selected as the sample. Data were gathered using a five-point Likert-scale questionnaire and analysed through multiple linear regression techniques. The findings show that AI-supported instruction exerts a significant and positive effect on student engagement. Likewise, self-regulated learning was also found to have a significant positive effect on student engagement. These findings highlight the dual importance of leveraging AI technology in teaching and strengthening student learning autonomy as strategies to foster deeper engagement. Theoretically, the study contributes to the growing body of literature on AI-enhanced pedagogy and learner autonomy in higher education. Practically, it provides guidance for educators and institutions to design learning models that

synergise technological support with self-regulated learning to enhance the quality of student engagement and academic outcomes in the digital era.
Keywords: *AI-Supported Teaching, Learning Autonomy, Student Engagement, Artificial Intelligence, Quantitative Study*

INTRODUCTION

Advances in science and technology during the Industrial Revolution 4.0 have significantly reshaped teaching and learning practices in higher education (Ismunandar, 2022). The educational process now involves the use of digital technology to increase access, improve quality, and enrich students' learning experiences. This means that this process no longer relies solely on conventional face-to-face interactions. In the field of education, the use of artificial intelligence (AI) has become one of the biggest innovations in recent years. AI is considered to have the ability to create a more personalized, adaptive, and effective learning system so that student involvement in the academic process increases (Chen et al., 2025). The integration of AI in education has been proven to be able to create a more interactive learning experience. Applications such as chatbots, adaptive learning systems, and big data-based learning analytics provide students with continuous learning support as well as direct feedback. Recent studies show that the use of AI in the classroom not only improves the quality of teaching, but also increases student motivation to learn, active participation, and student interaction with materials and lecturers (Frida Gjermeni, 2024). Nevertheless, issues such as the possibility of over-reliance on technology, ethical issues, and data privacy are still issues that need to be carefully considered (Talukder & bin Ahsan, 2025).

In addition to external factors such as technological support, internal student factors are also very important in determining their involvement. One of the important concepts is self-regulated learning (SRL), which is the ability of students to manage their own learning process independently (An et al., 2024; Gambo & Shakir, 2021). Students with high SRL tend to have the ability to set learning goals, choose the right strategies, monitor their progress, and evaluate their learning outcomes. Research shows that students with high SRL can better use digital, thermal, and thermal technologies (Frida Gjermeni, 2024). In religion-based higher education, such as Buddhist universities in Bandar Lampung, the challenges as well as opportunities in the application of AI and SRL are becoming increasingly complex. Buddhist education does not only emphasize the moral, spiritual, and character of the students. Therefore, student involvement in learning must be seen as a whole, which includes self-development and intellectual. The use of SRL can help students become more independent learners and responsible for the learning process carried out. On the other hand, the integration of AI in teaching can help lecturers improve the methods used in the learning activities they provide.

Student engagement is one of the key indicators of success in higher education. Students with high levels of engagement tend to demonstrate stronger learning motivation, better academic achievement, and higher levels of learning satisfaction. The study by Saputra and Hidayati (2023) shows that student engagement contributes to increased motivation and learning persistence. Siregar et al. (2022) found that high engagement is closely related to improved academic performance and active participation in the learning process. Meanwhile, Widodo et al. (2023) reported that student engagement, cognitively, affectively, and behaviorally, creates more meaningful learning experiences and supports academic success. In general, student engagement includes three main dimensions: cognitive, affective, and psychomotor engagement. Cognitive engagement is reflected in students' abilities to understand, critique, and apply the knowledge they acquire; affective engagement appears through students' interest and positive enthusiasm toward learning activities; while

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psychomotor engagement is evident in students' activeness in discussions, completing assignments, and participating in class activities.

Thus, increasing student involvement is a very important goal for every university (Ezeoguine & Eteng-Uket, 2024). A new study shows that students are more likely to favor the use of AI in learning, because the use of AI can help students, especially when the technology is combined with the right strategies. AI is not intended to replace the role of lecturers but to strengthen the interaction between lecturers and students and can also create learning that can make students perperitative (Karim et al., 2025). Thus, research on the influence of AI-supported teaching and self-regulated learning on student engagement in Buddhist universities in Bandar Lampung is very relevant and important. Although previous studies have examined AI or self-regulated learning separately, there remains a gap in understanding how these two factors jointly influence student engagement in religion-based higher education. This study offers novelty by investigating the combined effect of AI-based teaching and self-directed learning on students' academic engagement at a Buddhist university, providing new insights for educational practices that integrate technology and learner autonomy.

METHOD

This study employed an explanatory method to analyze the effects of AI-Supported Teaching and Self-Regulated Learning on Student Engagement among students at a Buddhist higher education institution in Bandar Lampung. The population consisted of 300 students, with a purposive sample of 171 respondents selected based on relevant criteria, such as active participation in AI-based courses and experience with self-directed learning. The instrument was a five-point Likert questionnaire, structured around the variables' indicators: AI-Supported Teaching (personalization, feedback, adaptive systems, interaction support), Self-Regulated Learning (goal setting, self-monitoring, self-efficacy, reflection, and learning strategies), and Student Engagement (behavioral, emotional, cognitive engagement). The questionnaire was distributed both online and in person to reach respondents with limited internet access. Instrument validity was assessed using the Corrected Item Total Correlation method, while reliability was evaluated through Cronbach's Alpha (≥ 0.7). Quantitative data analysis was performed using multiple linear regression, supported by classical assumption testing including normality, multicollinearity, heteroscedasticity, and autocorrelation to confirm the robustness of the model. All analyses were conducted with statistical software to ensure the results were valid, reliable, and scientifically interpretable.

RESULT AND DISCUSSION

Results

Prerequisite Test Results

Validity testing was performed to determine the degree to which each indicator within a variable was significantly associated with the measured construct. Table 1 displays the results of the Pearson correlation analysis among the three principal variables examined in this study, namely AI-supported teaching, self-regulated learning, and student engagement. This correlation analysis was conducted to confirm the consistency of the relationships among the variables, thereby ensuring that the instrument was appropriate for subsequent stages of analysis. The test involved 171 respondents.

Table 1. Validity Test

Correlations				
		AI-Supported Teaching	Self-Regulated Learning	Student Engagement
AI-Supported Teaching	Pearson Correlation	1	.875**	.652**
	Sig. (2-tailed)		.000	.000
	N	171	171	171
Self-Regulated Learning	Pearson Correlation	.875**	1	.578**
	Sig. (2-tailed)	.000		.000
	N	171	171	171
Student Engagement	Pearson Correlation	.652**	.578**	1
	Sig. (2-tailed)	.000	.000	
	N	171	171	171

**. Correlation is significant at the 0.01 level (2-tailed).

Source: data processed SPSS 23, 2025

Based on the validity test results shown in the correlation table above, all variables were found to have a significant relationship with the dependent variable, as presented in Table 1. AI-supported teaching shows a correlation coefficient of 0.652 with a significance value of 0.000, whereas self-regulated learning demonstrates a correlation coefficient of 0.578 with a significance value of 0.000. A significance value below 0.05 indicates that the relationship between each independent variable and the dependent variable is statistically meaningful. Therefore, the instruments used to assess AI-supported teaching and self-regulated learning can be considered valid.

Based on the test results listed in the Case Processing Summary and Reliability Statistics table, it can be explained that the amount of data analyzed in this study was 171 respondents with a data completeness level of 100%. There was no data taken out of the analysis process (excluded cases = 0; 0.0%), which indicates that all respondents gave complete answers to each item in the research instrument. The statement Listwise deletion based on all variables in the procedure shows that the system will automatically delete incomplete data, but in this study, this did not happen, so it can be concluded that the integrity of the data is maintained very well. These findings provide the basis for the reliability testing results presented in Table 2.

Table 2. Instrument Reliability Test

Reliability Statistics	
Cronbach's Alpha	N of Items
. 808	11

Source: Data processed SPSS 26, 2025

Based on the reliability statistics presented in Table 2, the Cronbach's Alpha value was 0.808 for a total of 11 items. This value reflects that the research instrument has an excellent level of reliability, as it exceeds the minimum recommended reliability standard, which is 0.70 (Nunnally & Bernstein, 1994). Thus, the instruments used are judged to have strong internal consistency, where each statement item is positively correlated with each other in measuring the same construct or variable. Overall, these results confirm that the research instruments used are reliable and feasible to be used in the next stage of analysis.

Classic Assumption Test

The normality test aims to determine whether the research variables follow a normal distribution. This test is important because normally distributed data influence the selection of appropriate statistical analyses. The criteria for assessing normality can be reviewed through

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the numerical values provided. Table 3 presents the results used to identify whether the data are normally distributed.

Table 3. Normality Test

One-Sample Kolmogorov-Smirnov Test		
		Unstandardized Residual
N		11
Normal Parameters[a,b]	Mean	.0000000
	Std. Deviation	1.42776704
Most Extreme Differences	Absolute	.045
	Positive	.045
	Negative	-.044
Test Statistic		.045
Asymp. Sig. (2-tailed)		.200[c,d]
a. Test distribution is Normal.		
b. Calculated from data.		
c. Lilliefors Significance Correction.		
d. This is a lower bound of the true significance.		

Source: Data processed SPSS 26, 2025

As shown in Table 3, the One-Sample Kolmogorov–Smirnov test results for the unstandardized residuals indicate that, with a sample of 171 observations, the mean value is 0 and the standard deviation is 1.43. The test produced a statistic of 0.045 with an asymptotic two-tailed significance value of 0.200 following the Lilliefors correction. Because this significance level exceeds the 0.05 criterion, it can be concluded that the residuals do not significantly deviate from a normal distribution. Thus, the residuals in this model are normally distributed. This result indicates that the normality assumption has been met, making the analytical model used, such as linear regression, appropriate to proceed without any indication of violation of the basic normality assumption.

Multicollinearity Test

The multicollinearity test is conducted to examine whether correlations exist among the independent variables. When the independent variables are correlated with one another, they are not orthogonal and, as a result, cannot be adequately analyzed using a regression model. The outcomes of the multicollinearity test are reported in Table 4 below.

Table 4. Uji Multikolinieritas

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Itself.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	Bright
1	(Constant)	2.583	.703		3.674	.000		
	AI-Supported Teaching	.486	.094	.627	5.188	.000	.234	4.270
	Self-Regulated Learning	.022	.094	.029	.239	.811	.234	4.270
a. Dependent Variable: Student Engagement								

Source: SPSS data processing results 23, 2025

Based on table 4, the results of the multiple linear regression analysis, the regression model obtained is as follows: y = 2.583 + 0.486x1 + 0.022x2. The constant value of 2.583

suggests that when the independent variables, AI-supported teaching and self-regulated learning, are held at zero, the predicted level of the dependent variable, student engagement, is 2.583. This value represents a baseline level of student engagement that is independent of the two predictor variables. AI-supported teaching has a regression coefficient of 0.486 with a significance value of 0.000, indicating a positive and statistically significant effect on student engagement. Interpretatively, every one-unit increase in AI-Supported Teaching will increase Student Engagement by 0.486 units, assuming other variables remain constant. The standardized beta coefficient of 0.627 shows that the relative contribution of AI-Supported Teaching to Student Engagement is the most dominant compared to the other independent variable. In contrast, self-regulated learning shows a regression coefficient of 0.022 with a significance value of 0.811, suggesting that this variable does not exert a statistically significant influence on student engagement.

Heteroscedasticity Test

The heteroscedasticity test is conducted to assess whether the regression model exhibits unequal variance among the residuals. Detecting variance disparities is important because heteroscedasticity can affect the accuracy of regression estimates. This test evaluates whether the residuals exhibit consistent spread across predicted values. The results of this heteroscedasticity analysis are presented in Table 5.

Table 5. Heteroscedasticity Test Coefficients

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.578	.401		3.932	.000
	AI-Supported Teaching	.003	.054	.008	.049	.961
	Self-Regulated Learning	-.016	.053	-.047	-.292	.770

a. Dependent Variable: absolute residual values (Abs_RES)

Source: SPSS data processing results 23, 2025

Table 5 shows the results of multiple linear regression analysis shown in the coefficient table, the regression model is as follows. The intercept value of 1.578 indicates that when the independent variables AI-Supported Teaching and Self-Regulated Learning are zero, the predicted value of the absolute residual (Abs_RES) is 1.578. The significance of the constant is 0.000 (< 0.05), indicating that the constant is significantly different from zero and plays a role in forming the regression model. AI-Supported Teaching has a regression coefficient (B) of 0.003, a t-value of 0.049, and a significance (Sig.) of 0.961. The significance value, which is well above 0.05, indicates that AI-supported teaching does not have a significant effect on the absolute residual (Abs_RES) of student engagement. The standardized Beta value of 0.008 is also very small, reinforcing the finding that the effect on the variation of absolute residuals is not statistically significant. Therefore, it can be concluded that changes in this variable do not contribute significantly to changes in the absolute residual values.

Meanwhile, Self-Regulated Learning has a regression coefficient (B) of -0.016, a t-value of -0.292, and a significance (Sig.) of 0.770. Similar to AI-Supported Teaching, the significance being greater than 0.05 indicates that it does not have a significant effect on the absolute residual (Abs_RES) of Student Engagement. The regression results show that neither AI-Supported Teaching nor Self-Regulated Learning significantly affects the absolute residual

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(Abs_RES) of student engagement. This indicates that the absolute residual values are not significantly influenced by the independent variables used in the model. Therefore, the regression model can be considered to meet the homoscedasticity assumption, as no significant relationship is found between the independent variables and the absolute residual values.

Autocorrelation Test

The autocorrelation test is used to examine whether, in a multiple linear regression model, there is a correlation between the error term at time t and the error term at time t−1 (the previous period). Autocorrelation was assessed using the Durbin–Watson (DW) test, and the results of this analysis are presented in Table 6 below.

Table 6. Runs Test

Runs Test	
	Unstandardized Residual
Test Value[a]	-.17927
Cases < Test Value	85
Cases >= Test Value	86
Total Cases	171
Number of Runs	77
Z	-1.457
Asymp. Sig. (2-tailed)	.145

a. Median

Source: SPSS data processing results 23, 2025

Based on the results shown in Table 6, the Runs Test is used to examine the assumption of residual independence, specifically to determine whether the residuals (errors) in the regression model occur randomly. Randomly distributed residuals indicate the absence of autocorrelation in the regression model, suggesting that the model is appropriate for predictive analysis. The result shows a value of Z = -1.457 with Asymp. Sig. (2-tailed) = 0.145. This significance value is greater than 0.05 (0.145 > 0.05), so it can be concluded that there is no autocorrelation or systematic pattern in the residual distribution. In other words, the residual model is random. Test Value = -0.17927 indicates the median of the residual used as a delimiter between the residual below and above the value. There were 85 cases with residual values below the median and 86 cases above the median, with a total of 171 observations. Meanwhile, the number of runs (alternation between positive and negative residuals) was 77, which was within a reasonable range according to the expectations of random data.

Multiple Linear Regression Test

Multiple regression is an appropriate analytical technique when a study includes one dependent variable that is presumed to be related to one or more independent variables. The objective of multiple linear regression analysis is to estimate changes in the dependent variable in response to the independent variables. In this study, multiple linear regression was performed using the SPSS software, and the results of the analysis are presented in Table 7.

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Table 7. Regression Coefficients

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.583	.703		3.674	.000
	Ai-supported teaching	.486	.094	.627	5.188	.000
	Self-regulated learning	.022	.094	.029	.239	.811

a. Dependent Variable: Student engagement

Source: SPSS data processing results 26, 2025

Tabel 7 shows the results of multiple linear regression analysis presented in the coefficient table, the regression equation model was obtained as follows:
y=2.583+0.486x1+0.022x2. The value of the constant (intercept) of 2.583 indicates that if the independent variable Ai-supported teaching and self-regulated learning are zero, then the predicted value of the dependent variable y is 2.583. A significance value of a constant of 0.000 (< 0.05) indicates that the constant differs significantly from zero, so it can be interpreted that the regression model has a statistically significant base value. Ai-supported teaching has an unstandardized regression coefficient (B) of 0.486, with a value of t = 5.188 and a significance value (Sig.) of 0.000. A significance value smaller than 0.05 indicates that x1 has a positive and significant influence on the dependent variable y. That is, everyone unit increase in Ai-supported teaching will increase the y-value by 0.486 units, assuming that the other variable is in a constant state. In addition, the standardized Beta coefficient value of 0.627 indicates that Ai-supported teaching makes a dominant contribution in explaining the variation in Student engagement.

Meanwhile, the Self-regulated learning has a regression coefficient (B) of 0.022, with a value of t = 0.239 and a significance value of 0.811. A significance value much greater than 0.05 indicates that Self-regulated learning has no significant effect on the dependent variable y. Although the direction of influence is positive, the relationship between Self-regulated learning and Student engagement is not statistically strong enough to be declared meaningful. Thus, the variable does not make a meaningful contribution in explaining the variation in the value of student engagement.

Hypothesis Test Results

The simultaneous test (F-test) is conducted to examine the combined effect of the independent variables on the dependent variable. This test is important because it determines whether the regression model as a whole is statistically significant. The F-test calculation is obtained from the ANOVA table produced through SPSS data processing, and the results of this analysis are presented in Table 8.

Table 8. Anova

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	363.463	2	181.732	62.229	.000[b]
	Residual	490.619	168	2.920		
	Total	854.082	170			

a. Dependent Variable: Student engagement

b. Predictors: (Constant), Ai-supported teaching, self-regulated learning

Source: SPSS data processing results 23, 2025

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Based on table 8, the results of the ANOVA (Analysis of Variance) test shown in the table above, it can be explained that this analysis aims to test the simultaneous significance or influence of the joint between Ai-supported teaching and self-regulated learning on Student engagement. The results of the test indicate an F value of 62.229 with a significance level (Sig.) of 0.000. Since this significance value is below 0.05, the regression model employed in this study is statistically significant, indicating that AI-supported teaching and self-regulated learning simultaneously influence student engagement.

The Sum of Squares Regression value of 363,463 illustrates the magnitude of the variation of the dependent variable (Student engagement) that can be explained by a regression model involving independent variables (Ai-supported teaching and self-regulated learning). Meanwhile, the Sum of Squares Residual value of 490.619 indicates a magnitude of variation that cannot be explained by the model, or in other words, variations caused by factors other than the variables under study. The Mean Square Regression value of 181.732 is derived by dividing the Regression Sum of Squares by its degrees of freedom (df = 2), while the Mean Square Residual value of 2.920 results from dividing the Residual Sum of Squares by its degrees of freedom (df = 168). From a statistical perspective, these findings indicate that the regression model has a significant capacity to explain variations in student engagement.

The t-test aims to determine the extent to which each independent variable individually influences the dependent variable. This test is important because it evaluates the significance of each predictor within the regression model. The t-test results are generated through SPSS data processing and provide evidence of the partial effects of each variable. The detailed outcomes of this partial analysis are presented in Table 9.

Tabel 9. Koefisien

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.583	.703		3.674	.000
	x1	.486	.094	.627	5.188	.000
	self-regulated learning	.022	.094	.029	.239	.811

a. Dependent Variable: y

Sumber: Hasil olah data SPSS 26, 2025

Table 9 shows the results of the multiple linear regression coefficient test in the Coefficients table above, the regression equation formed is as follows: Y=2.583+0.486X1+0.022X2

These results show a constant value (B = 2.583), which means that if *AI-supported teaching* and *self-regulated learning* are valued at zero, then the *student engagement* score (Y) is at 2.583. In other words, there is a baseline value of variable Y that is not influenced by the two independent variables. Furthermore, the regression coefficient for AI-supported teaching is 0.486, with a t-value of 5.188 and a significance level of 0.000 ($p < 0.05$), indicating a positive and statistically significant effect on student engagement. This suggests that a one-unit increase in AI-supported teaching is associated with a 0.486-unit increase in student engagement, assuming other variables are held constant. Additionally, the standardized beta coefficient of 0.627 demonstrates that AI-supported teaching makes a strong and significant contribution to

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explaining variations in student engagement, showing a relatively greater influence compared to the other predictor variable.

Meanwhile, *self-regulated learning* has a regression coefficient of 0.022, with a t-value of 0.239 and a significance level of 0.811 (> 0.05). These results show that *self-regulated learning* does not have a significant effect on *student engagement*. Although the direction of influence is positive, the contribution of *self-regulated learning* to changes in *student engagement* is not statistically strong enough to be considered significant. Overall, this analysis indicates that the regression model used is feasible, but the dominant influence on *student engagement* comes only from *AI-supported teaching*, while *self-regulated learning* does not provide a meaningful effect. Thus, it can be concluded that *AI-supported teaching* is the main predictor in this model, significantly influencing *student engagement* based on the partial test (t-test).

Discussion

The findings of this study reveal that AI-supported teaching exerts a positive and statistically significant influence on student engagement, while self-regulated learning (SRL) does not demonstrate a significant effect. Simultaneously, both independent variables have a significant influence on student engagement based on the F-test ($F = 62.229$; $p < 0.001$), but individually only AI-Supported Teaching provides a dominant contribution ($\beta = 0.627$). These findings suggest that the use of artificial intelligence technology in the learning process functions not only as a technical tool but also as an active pedagogical agent capable of enhancing students' participation, motivation, and focus during learning. Conversely, self-regulation skills have not demonstrated a significant role within AI-mediated learning contexts.

The Effect of AI-Supported Teaching on Student Engagement

These results are consistent with previous studies showing that the integration of AI in learning can enhance interactivity, personalization, and instructional effectiveness. Chen and Zhang (2022) highlight that AI contributes to improved instructional processes, while Zawacki-Richter et al. (2019) emphasize its role in increasing personalization and interactivity. AI-based systems enable content to be adapted to individual needs, provide rapid automated feedback, and promote more intensive interaction between students and learning materials. Kim and Wang (2023) support this by noting that AI-driven environments enable richer student–content interaction. Thus, the increase in student engagement can be explained through three main mechanisms: 1. Personalized learning in the context of artificial intelligence allows the system to analyze students' behavioral patterns, preferences, and individual abilities in real time, enabling the difficulty level, type of learning resources, and sequencing of content to be dynamically adjusted to each learner's profile. Through this mechanism, students no longer receive a "one-size-fits-all" approach but instead experience adaptive learning tailored to their cognitive and emotional needs. 2. Adaptive feedback generated by AI strengthens students' perceived competence and motivation by providing instant responses to their performance, whether in the form of automated assessment, improvement recommendations, or contextual adjustments in learning strategies. This process encourages students to recognize their progress more concretely and fosters a desire to continue improving their achievements. 3. Autonomy-centered learning is reflected in the AI system's ability to provide students with the freedom to choose learning pathways, pace, and resources, thereby enhancing their sense of ownership over the learning process.

These three elements, personalization, adaptive feedback, and autonomy, work synergistically to create a learning experience that is not only cognitively efficient but also affectively meaningful, ultimately strengthening overall student engagement in AI-based learning environments. Recent research has shown that AI-based adaptive learning systems are able to tailor materials and feedback to individual needs, thereby increasing students' motivation, engagement, and perceived self-control over their learning process (Hidayat et al., 2025). From a theoretical perspective, these findings align with the Self-Determination Theory (Deci & Ryan, 2000), which posits that learning engagement is shaped by the satisfaction of psychological needs for autonomy, competence, and social relatedness. AI contributes to these dimensions by offering personalized feedback, adaptive learning environments, dynamic assessments, and responsive interactions that are tailored to the individual needs of learners (Dai et al., 2025).

The Effect of Self-Regulated Learning on Student Engagement

The finding that SRL does not have a significant effect on Student Engagement ($\beta = 0.022$; $p = 0.811$) contrasts with classical theories such as Panadero (2017), which emphasize the importance of self-regulation skills in driving learning engagement. However, in the context of AI-based learning, this result can be explained by the shift of regulatory functions from humans to intelligent systems. AI often provides automated guidance, recommended learning steps, and progress monitoring, thereby reducing students' need to manage their learning strategies independently (Chen & Zhang, 2022). In other words, AI systems take over a substantial portion of the cognitive and metacognitive regulatory processes that are typically carried out by individuals. In addition, students' readiness to utilize advanced technologies can be a limiting factor. According to Rahman et al. (2023), technology does not automatically enhance self-regulation if users lack sufficient metacognitive awareness or intrinsic motivation. Therefore, it is important for institutions to balance the implementation of intelligent technologies with training in independent learning strategies to ensure that the human role remains essential in digital learning environments.

Theoretically, this study draws on two primary conceptual frameworks: the Technology Acceptance Model (TAM) and Self-Regulated Learning Theory (SRL Theory). TAM continues to be relevant in technology-driven learning contexts; for instance, recent studies have indicated that self-regulated learning and technological affinity significantly affect perceived usefulness and perceived ease of use in e-learning within higher education (Barz et al., 2024). In this study, AI-Supported Teaching is represented as a concrete manifestation of perceived usefulness and ease of use, where students tend to be more engaged when AI-based systems are perceived to improve efficiency, comprehension, and the overall learning experience. Meanwhile, SRL theory remains relevant in the context of AI-enhanced learning, as recent research has shown that AI can support learners' self-regulation phases such as planning, implementation, and reflection, although its success depends heavily on how the AI system is integrated to maintain student autonomy (Yao & Liu, 2025).

However, the empirical findings of this study show that the technology-based variable (AI-Supported Teaching) has a stronger and more significant effect compared to the psychological variable (Self-Regulated Learning). This indicates a shift in dominance from internal factors toward external factors in influencing student engagement in the digital learning era. AI, as a pedagogical entity, has taken over part of the regulatory functions previously carried out by individuals by providing scaffolding, instant feedback, and automatic content adaptation. As a result, student engagement is more strongly driven by the design of intelligent and responsive learning systems rather than by traditional self-regulation strategies. This phenomenon marks the emergence of a new paradigm in modern education, where learning success is no longer determined solely by internal cognitive capacities but also by the extent to

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which digital learning systems are able to create adaptive, personalized, and interactive learning ecosystems.

Moreover, the outcomes of the classical assumption tests, including normality, multicollinearity, heteroscedasticity, and autocorrelation, demonstrate that the regression model employed is valid, reliable, and satisfies the requirements for statistical inference. With these assumptions fulfilled, the causal relationship between the independent and dependent variables in this study can be interpreted validly and without bias. This means that the significant influence of AI-Supported Teaching on Student Engagement is not the result of data anomalies or assumption violations, but instead reflects a consistent and measurable empirical relationship. Methodologically, this strengthens the external validity of the model and ensures that the theoretical interpretation produced has a strong empirical foundation for explaining the reality of AI-based learning in higher education settings.

Overall, this study confirms that AI-Supported Teaching is the primary predictor that significantly increases Student Engagement, whereas Self-Regulated Learning has not shown a significant effect in technology-mediated learning contexts. These findings highlight the importance of balancing technological innovation with the development of students' independent learning competencies. The success of AI implementation in education is not determined solely by the sophistication of the system, but also by pedagogical efforts to ensure that technology functions as an empowering tool rather than a replacement in human learning processes. AI-Supported Teaching and Self-Regulated Learning Simultaneously Influence Student Engagement in Higher Education. Based on the table above, the results of the simultaneous test calculation show that the calculated F value is 62.229. While seen from the significance rate of 0.000. This means that the significance value of the simultaneous test of 0.000 is smaller than 0.05, it can be concluded that there is a significant influence together between the independent variables, namely artificial intelligence-supported teaching and learning independence on the variable of student engagement in higher education. AI-Supported Teaching and Self-Regulated Learning Partially Influence Student Engagement in Higher Education. The discussion of the partial (t-test) results based on the table above using SPSS can be explained as follows: Based on the partial calculation, the t-value for the AI-supported teaching variable is 5.188 with a significance level of 0.000. This means that the AI-supported teaching variable has a positive and significant effect on student engagement in higher education. Based on the partial calculation, the t-value for the self-regulated learning variable is 0.239 with a significance level of 0.811. This means that the self-regulated learning variable has a positive and significant effect on student engagement in higher education. The conclusion from the partial results above is that each independent variable, AI-supported teaching and self-regulated learning, has a positive and significant effect on the dependent variable, student engagement

CONCLUSSION

The study concludes that the integration of artificial intelligence plays a central role in increasing student engagement in higher education. Simultaneous regression results show that AI-Supported Teaching and Self-Regulated Learning jointly influence engagement, but only AI-Supported Teaching has a statistically significant positive effect. This indicates that AI-based systems, through interactivity, personalization, and adaptive support, become the main driver of cognitive, affective, and behavioral engagement, while the influence of self-regulation diminishes as AI increasingly assumes monitoring and control functions in learning.

Overall, AI-supported teaching emerges as the key predictor of student engagement, highlighting the need for institutions to design AI-based learning that remains human-centered.

AI should strengthen autonomy, reflection, and intrinsic motivation rather than replace human learning processes. Therefore, educators are encouraged to integrate AI pedagogically and ethically, design activities that foster independent learning, use AI to enhance interaction and provide adaptive feedback, ensure authentic learning assessment, and promote AI literacy for both lecturers and students.

Practically, the success of AI integration depends on combining technological sophistication with strategies that enhance students' motivation and autonomy. Theoretically, the findings show a shift in learning regulation from the individual toward digital systems, expanding the perspectives of Self-Regulated Learning Theory and the Technology Acceptance Model. This opens opportunities for further research on how AI-based learning designs can balance efficiency, academic integrity, and the development of critical and reflective thinking in the digital era.

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