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The Effect of Artificial Intelligence (AI) Technology Use and Learning Motivation on Student Academic Achievement in Higher Education

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Abstract

This study analyses the effect of the use of Artificial Intelligence technology and learning motivation on student academic achievement. The sample consisted of 162 active students drawn from each semester level of the Nautical Science, Marine Engineering, and Maritime Transport and Port Management (KALK) study programmes, with data collected through a questionnaire. Data were analysed in SmartPLS 4 using a path analysis approach to test the relationships between variables. The results show that the use of AI technology has a positive and significant effect on student academic achievement, with a path coefficient of 0.275 (p = 0.000). Learning motivation also has a positive and significant effect and is the most dominant variable, with a path coefficient of 0.703 (p = 0.000). The model explains 72.6% of the variance in student academic achievement. It can therefore be concluded that the use of AI technology and learning motivation are important factors in improving academic achievement among students of the Nautical Science, Marine Engineering, and KALK study programmes at the Maritime Institute of Jakarta.

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1. INTRODUCTION

The development of information and communication technology in the present digital era has brought significant change to many aspects of life, including higher education. One of the innovations developing most rapidly is Artificial Intelligence (AI) technology, which can support teaching and learning processes in becoming more interactive, adaptive and effective. The use of AI in the academic environment allows students to access learning material quickly, to run simulations, and to obtain more personalised feedback. This has an indirect effect on the quality of the learning process and on student learning outcomes. The use of AI technology has therefore become an important focus in the development of modern education.

Besides technological factors, learning motivation is an important component affecting student academic achievement. Learning motivation relates to the internal drive of students to reach academic goals, such as completing assignments, understanding course material, and developing new skills. Students with high learning motivation tend to be more active, disciplined and consistent in following the learning process. This

condition has a direct effect on the attainment of better academic achievement. Learning motivation is thus a crucial factor in improving the effectiveness of student learning.

Student academic achievement is an indicator of the success of higher education and of the quality of an institution's graduates. Academic achievement is influenced not only by the intellectual ability of students, but also by the learning environment, technological support, and psychological factors such as learning motivation. Understanding the factors that affect academic achievement is therefore very important for developing more effective learning strategies. Research on the effect of AI technology use and learning motivation on academic achievement can contribute to the design of appropriate academic policy.

In the digital era, students are required to make optimal use of technology in support of their academic activities. The use of AI technology can help students access material independently, carry out interactive exercises, and simplify the process of learning evaluation. With the assistance of AI, students can learn according to their own style and pace, so that the potential for attaining academic achievement can increase. This study takes the view that the use of AI technology is not merely a support tool, but also a factor capable of affecting student motivation and learning effectiveness.

Student learning motivation is often influenced by personal interest, academic goals, and encouragement from the surrounding environment. Students with high motivation tend to absorb information more easily, complete assignments on time, and participate actively in academic activities. The link between learning motivation and academic achievement has been demonstrated by many previous studies. However, the combination of AI technology use and learning motivation has been little examined, particularly in the context of students in the Nautical Science, Marine Engineering, and KALK study programmes. This forms an important background for further research.

This study was conducted on 162 active student respondents from the Nautical Science, Marine Engineering, and KALK study programmes, with data collected through a questionnaire. The selection of respondents was carried out in order to obtain a representative picture of the effect of AI technology use and learning motivation on academic achievement. The analytical method used is path analysis based on SmartPLS version 4, which is able to analyse relationships between latent variables measured through questionnaire indicators. This approach was chosen because it is suited to social and educational research involving complex variables.

The problem formulation of this study focuses on three main questions: whether the use of AI technology affects student academic achievement; whether learning motivation affects student academic achievement; and which variable is more dominant in affecting student academic achievement. These questions were formulated to give a clear direction to the analysis and to connect theory, variables and the phenomena observed in the field. This problem formulation forms the basis for the research objectives and the methodology employed.

The objective of this study is to analyse the effect of AI technology use and learning motivation on student academic achievement, and to identify the variable that is most dominant in affecting academic achievement. The study is expected to make a scientific contribution by explaining the relationship between technology, motivation and student learning outcomes. In addition, the results may serve as practical input for the institution and for lecturers in designing effective learning strategies. The study emphasises the importance of integrating AI technology with efforts to raise learning motivation.

The benefits of this study are both theoretical and practical. Theoretically, the study provides an understanding of the relationship between AI technology use, learning motivation, and student academic achievement. Practically, the results can be used as a reference for developing technology-based learning strategies and for raising learning motivation within the Nautical Science, Marine Engineering, and KALK study programmes. The study is thus expected to contribute to improving the quality of higher education and student academic achievement.

2. METHOD

The research method was designed to test the effect of the use of Artificial Intelligence (AI) technology and learning motivation on student academic achievement. The method adopts a quantitative approach with a descriptive and analytical research design. The details of the research method are as follows:

- Research Design

  This study uses a quantitative design with a survey approach. This approach was chosen because the objective of the research is to analyse quantitatively the effect of the use of Artificial Intelligence technology (X1) and learning motivation (X2) on student academic achievement (Y). A quantitative design allows the researcher to measure relationships

between variables using numerical data obtained from a questionnaire.

In addition, this study uses path analysis based on PLS-SEM through SmartPLS 4. This method is appropriate because the research variables are latent variables measured through questionnaire indicators. Path analysis allows the researcher to test the direct effect and the relative dominance of each independent variable on the dependent variable.

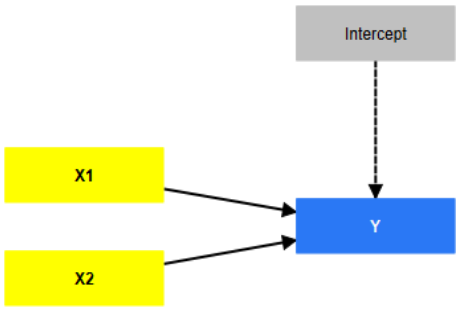


Figure 1. Research design

- Population and Sample

The population of this study comprises active students attending classes in the odd semester of 2025–2026 in the Diploma IV Nautical Science, Marine Engineering, and KALK study programmes.

The sample was drawn by random sampling at each semester level, namely semesters 3, 7 and 8. The sample size taken is approximately 162 students in order to ensure the representativeness and accuracy of the research results.

3. RESULTS AND DISCUSSION

Results

Classical Assumption Testing Criteria

In classical assumption testing within SEM-PLS, the statistical tests are carried out in several stages. The stages of classical assumption testing are presented in the table below.

Table 1. Classical assumption testing criteria

Statistical Test	Test Criterion	Conclusion
Multicollinearity	VIF < 10	Pass
	VIF > 10	Fail
Heteroscedasticity	P value < 0.05	Fail
	P value > 0.05	Pass
Autocorrelation (secondary data)	DU < DW < 4-DU	Pass

The output of the data processing yields collinearity statistics – VIF values below 10 for every variable, which means that the collinearity assumption is satisfied, as shown in Table 2.

Table 2. Collinearity statistics – VIF

	VIF
X1	1.435
X2	1.435

The next stage applies the Breusch–Pagan test to determine whether heteroscedasticity is present.

Table 3. Breusch–Pagan test

	Test-Statistic	*df*	*P value*
Breusch–Pagan test	9.187	2	0.623

The Breusch–Pagan test above gives a P value of 0.623, which is greater than 0.05, so that the heteroscedasticity assumption is also satisfied.

The autocorrelation test is subsequently disregarded because the study uses cross-sectional data rather than time-series or secondary data.

Multiple Linear Regression Testing Criteria

Multiple linear regression testing is carried out in two stages, namely the t-test (partial test) and the F-test (simultaneous test). The t-test is used to determine the effect of each variable used, whereas the F-test is used to determine the effect of the variables simultaneously. These are shown in Table 4, the criteria for multiple linear regression testing, below.

Table 4. Multiple linear regression testing criteria

Statistical Test	Test Criterion	Conclusion
t-test (partial test)	P value < 0.05	Significant effect
	P value > 0.05	No significant effect
F-test (simultaneous test)	P value < 0.05	Significant simultaneous effect
	P value > 0.05	No significant simultaneous effect

The output of the data processing gives P values for variables X1 and X2 that are smaller than 0.05, which means that they have a significant effect on the dependent variable.

Table 5. t-test (partial test)

The results of the F-test (simultaneous test) give P values for variables X1 and X2 that are smaller than 0.05, which means that they have a simultaneous and joint effect.

Table 6. F-test (simultaneous test)

	Sum square	*df*	*Mean square*	*F*	*P value*
Total	53.609	161	0.000	0.000	0.000
Error	14.511	159	0.091	0.000	0.000
Regression	39.098	2	19.549	214.203	0.000

The next stage is the coefficient of determination test, examining the adjusted R-square value of 0.726. This means that the independent variables X1 and X2 jointly contribute 72.6% of the variation in the dependent variable. The remaining 27.4% is influenced by other factors outside the model.

Table 7. *R-square*

	Y
R-square	0.729
R-square adjusted	0.726
Durbin–Watson test	1.733

Discussion

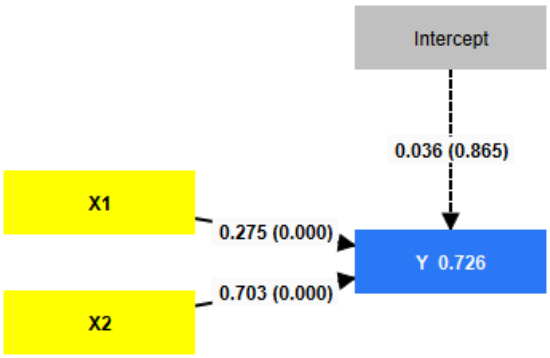


Figure 2. SEM-PLS output

The PLS analysis shows that the regression coefficient of the Artificial Intelligence Technology Use variable (X1) is positive, at 0.275, which means that as the Artificial Intelligence Technology Use variable (X1) increases, the Student Academic Achievement variable (Y) also increases. The Learning Motivation variable (X2) likewise shows a positive regression coefficient, at 0.703, which means that as the Learning Motivation variable (X2) increases, the Student Academic Achievement variable (Y) also increases. Between the two variables, Learning Motivation (X2) is the more influential factor in explaining change in the Student Academic Achievement variable (Y).

The R-square value for variable Y is 0.726, which means that the independent variables Artificial Intelligence Technology Use (X1) and Learning Motivation (X2) jointly and simultaneously account for 72.6% of the dependent variable Student Academic Achievement (Y). The remaining 27.4% is influenced by other variables not included in the research model. The model has strong explanatory power, indicating that the use of AI technology and learning motivation are significant factors in shaping student academic achievement.

4. CONCLUSION

The results of this study show that the use of Artificial Intelligence technology has a positive and significant effect on student academic achievement. Learning motivation is also shown to have a positive and significant effect, and is the most dominant variable in raising academic achievement. The research model explains 72.6% of the variance in student academic achievement through these two variables. The findings confirm that student academic success is strongly influenced by the combination of AI technology use and the level of learning motivation. Strengthening student competence in using AI technology, together with reinforcing learning motivation, can therefore serve as an important strategy for encouraging more optimal academic achievement.

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