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The Relationship between the Utilization of Artificial Intelligence Technology and the Learning Independence of STIKes Muhammadiyah Bojonegoro Students

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ABSTRACT

This study aims to analyze the relationship between the use of Artificial Intelligence (AI) technology and the learning independence of STIKes Muhammadiyah Bojonegoro students. The research used a quantitative approach with a cross-sectional analytical survey design. Out of the 158 responses collected, 13 multiple responses were issued so that 145 unique and complete responses were analyzed. The instrument consists of 25 five-level Likert scale items that measure usage intensity, utilization patterns, ease, effectiveness, dependence on AI, and learning independence. Data were analyzed using descriptive statistics, item-total correlation, Cronbach's Alpha, multiple linear regression of the Enter method, and bootstrap BCa as many as 5,000 resamples. The regression model was significant, F(5.139) = 8.240, p < 0.001, with R2 = 0.229 and adjusted R2 = 0.201. The intensity of AI use was positively and significantly related to learning independence, while the patterns of utilization, ease, and effectiveness did not show a significant partial relationship. The reliance on AI shows indications of negative relationships that need to be interpreted carefully as the significance of bootstrap is at a marginal boundary. Research concludes that AI can support independent learning when used as an aid, not as a substitute for students' thinking processes. Universities need to strengthen AI literacy, information verification, academic integrity, and process-based assessments.

1. INTRODUCTION

The development of Artificial Intelligence (AI) has changed the way students obtain information, understand material, organize assignments, improve writing, and receive feedback. In higher education, AI is used through chatbots, virtual assistants, adaptive learning, intelligent tutoring systems, learning analytics, recommendation systems, and automated assessments (Ambele, Kaijage, Dida, Trojer, & Kyando, 2022; Hughes, 2021; Nagaraj et al., 2023) This technology provides fast, flexible, and increasingly personalized support, so that students can ask for explanations, find sources, practice, or revise work without always waiting for direct interaction with lecturers (Alshahrani, Pileggi, & Karimi, 2024; Fernández-Herrero, 2024). Adaptive learning systems and intelligent tutors can also tailor materials, exercises, and feedback to the needs of users (Lyanda et al., 2024; R, 2025). In practice, the utilization of AI is not only determined by the presence or absence of use, but also by the frequency, type of academic activities assisted, convenience, and perceived benefits (Bozkurt, Karadeniz, Bañeres, Guerrero-Roldán, & Rodríguez, 2021; Harry & Sayudin, 2023; X. Wang et al., 2024). Therefore, AI utilization needs to be analyzed as a multidimensional construct, not as a single behavior. These changes are related to learning independence, which is the ability of students to set goals, manage time, choose sources, determine strategies, monitor progress, evaluate results, and take responsibility for their academic decisions

(Linnes, Ronzoni, Agrusa, & Lema, 2022; Lv & Li, 2024). Learning independence intersects with learning autonomy, independent learning, self-management learning, but that doesn't mean students have to learn without help. Students can still use the support of lecturers, friends, family, and technology as long as they maintain control over their learning goals and processes (Quintero, Poblete-Valderrama, & Quiroga, 2024). Online and blended environments increase these demands due to the flexibility of time and resources while shifting some of the learning responsibilities to students (Razali & Mohamad Nasri, 2023; Tripolca, 2023). Self-confidence, motivation, self-control, lecturer support, and the quality of the digital environment also determine the success of students in managing learning (Dai et al., 2024; Zou, Ping, & Jin, 2021).

AI can support self-reliance by providing access to resources, explanations, exercises, personalization, and feedback that allow students to continue learning as needed. The use of AI for material preview, problem exploration, data analysis, and job evaluation can strengthen students' roles as active learners (YAN & CHENG, 2022; Yin, Li, & Yu, 2023). Automated feedback can also speed up the identification of errors and improvement of learning strategies. However, ease and productivity do not always reflect a deep understanding. AI can generate answers that seem convincing but are wrong, biased, or accompanied by fictitious references, so students still have to check the source and assess its validity (Le Lagadec, Jackson, & Cleary, 2024; Michel-Villarreal, Vilalta-Perdomo, Salinas-Navarro, Thierry-Aguilera, & Gerardou, 2023; Shoja, Van de Ridder, & Rajput, 2023). When AI replaces reading, reasoning, writing, and evaluating, such use can drive dependence, decreased critical thinking, and weakened self-learning (Allison et al., 2025). The literature shows two trends that have not been fully resolved: AI as a supporter of independence and AI as a source of dependence. Previous studies have largely addressed personalization, technology acceptance, learning outcomes, or integrity risks separately, while empirical evidence testing multiple dimensions of simultaneous utilization is still needed. This gap is important in health education because students are not only required to produce assignments, but also verify information, assess evidence, solve problems, and make decisions responsibly (Le Lagadec et al., 2024; Veras et al., 2024). The institutional context is also important because policies, academic culture, lecturer support, and digital readiness can differ between campuses. This study offers novelty by examining the intensity of use, utilization patterns, ease, effectiveness, and dependence on AI in a single model in health college students. The purpose of the study is to analyze the simultaneous and partial relationship of the five dimensions with the learning independence of STIKes Muhammadiyah Bojonegoro students. The formulation of the problem is whether the use of AI as a whole and each of its dimensions is related to student learning independence.

2. METHODS

This study uses a quantitative approach with a cross-cutting analytical survey design. The population includes students of STIKes Muhammadiyah Bojonegoro batches of 2024 and 2025. Samples were obtained through nonprobability voluntary response sampling. Of the 158 respondents, 13 of them were dual respondents. So that the final sample amounted to 145 respondents. The instrument was in the form of a 25-item closed questionnaire with a Likert scale of 1= strongly disagree to 5= strongly agree. The use of AI consists of intensity of use (X1), utilization pattern (X2), convenience (X3), effectiveness (X4), and dependency (X5), each of four items. Learning independence (Y) is measured by five items regarding planning, efforts to understand the material, completing assignments, self-evaluation, and academic responsibility. Variable scores are calculated by summing items in the same dimension. The data is encoded and tabulated using Microsoft Excel, and then analyzed in SPSS. Validity is tested through Pearson's item-total correlation and internal consistency through Cronbach's Alpha. The analysis included descriptive statistics, residual

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normality tests of Kolmogorov-Smirnov and P-P Plot, multicollinearity via Tolerance and VIF, heteroscedasticity via Glejser, residual independence via Durbin-Watson, and influential observations via Cook's Distance. The hypothesis was tested using multiple linear regression of the Enter method at alpha = 0.05. Due to the significant residual normality test, the coefficient was equipped with bootstrap BCa 5,000 resamples with a 95% confidence interval.

3. RESULTS AND DISCUSSION

A total of 145 responses were analyzed after 13 multiple responses were excluded from the initial 158 responses. All items had a significant item-total correlation ($p < 0.001$), with a range of 0.513-0.912. Cronbach's Alpha value is in the range of 0.636-0.892. The highest average per item was found in the pattern of AI utilization (4,033), followed by learning independence (3,959), effectiveness (3,834), ease (3,538), intensity (3,029), and dependency (2,693). A summary of validity, reliability, and descriptive statistics is presented in Table 1.

Table 1. Validity, reliability, and descriptive statistics

Variable	r item-total	Alpha	Min-Max	Red	SD	Mean/item
X1 Intensity	0,565-0,795	0,699	5-20	12,117	2,605	3,029
X2 Utilization patterns	0,716-0,821	0,756	11-20	16,131	1,676	4,033
X3 Convenience	0,513-0,822	0,636	9-20	14,152	1,905	3,538
X4 Effectiveness	0,788-0,875	0,855	9-20	15,338	2,193	3,834
X5 Dependencies	0,783-0,912	0,892	4-20	10,772	3,244	2,693
Y Learning independence	0,664-0,724	0,728	16-25	19,793	1,810	3,959

The The Kolmogorov-Smirnov test on the residual yields $D = 0.087$ and $p = 0.009$, while the P-P Plot shows most of the points are around the diagonal line. Tolerance value 0.563-0.842 and VIF 1.188-1.776. The Glejser test was insignificant, $F = 0.638$ and $p = 0.671$. The Durbin-Watson value is 2.109, the maximum Cook's Distance is 0.202, and the standardized residual is in the range of -2.549 to 2.866. These results are used as the basis for the application of regression and a complement to bootstrap. The regression model was significant, $F(5.139) = 8.240$, $p < 0.001$, with $R = 0.478$, $R2 = 0.229$, adjusted $R2 = 0.201$, and standard error of estimate = 1.618. The regression equation is $Y = 12.518 + 0.171X1 + 0.172X2 + 0.116X3 + 0.120X4 - 0.098X5$. Intensity of use was positively and significantly associated with learning independence ($B = 0.171$; beta = 0.246; $p = 0.011$), while dependence showed a negative coefficient on conventional regression ($B = -0.098$; beta = -0.176; $p = 0.032$). The pattern of utilization, convenience, and effectiveness is not partially significant. Bootstrap corroborated the intensity results (BCa 95% 0.048-0.287; $p = 0.008$), while dependency had a BCa interval of -0.202 to -0.007 with bootstrap $p = 0.065$. The complete coefficients are presented in Table 2.

Table 2. BCa 95% regression and bootstrap coefficient

Predictors	B	OR	beta	t	p	BCa 95%	p boot
Constant	12,518	1,442	-	8,678	<0.001	9,631; 16,055	<0.001
X1 Intensity	0,171	0,066	0,246	2,580	0,011	0,048; 0,287	0,008
X2 Pattern	0,172	0,096	0,159	1,802	0,074	-0,030; 0,348	0,083
X3 Convenience	0,116	0,094	0,122	1,229	0,221	-0,051; 0,273	0,175
X4 Effectiveness	0,120	0,078	0,145	1,544	0,125	-0,060; 0,326	0,219
X5 Dependencies	-0,098	0,045	-0,176	-2,167	0,032	-0,202; -0,007	0,065

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Discussion

The Significant regression models show that the use of AI together is related to student learning independence. However, an R2 of 0.229 means the model only explains 22.9% of the independence variation, so AI is not the only determinant. Learning independence is a complex construct that is also influenced by self-regulation, self-efficacy, motivation, self-control, lecturer support, social support, and the quality of the learning environment (Rocha, Cabral, Chen, Rodriguez, & Yancy, 2022; Zou et al., 2021). This value is important because it prevents overinterpretation that the use of technology automatically results in independent students. The results of the study more accurately show that AI is one of the components in the learning ecosystem. The simultaneous findings support the view that AI utilization needs to be assessed through a combination of frequency, academic function, ease, benefit, and dependency, rather than just user or non-user status (Hughes, 2021; X. Wang et al., 2024). The significance of the model also shows that the direction of the relationship is not uniform. Intensity is positively related, dependence tends to be negative, while the other three dimensions do not have a significant partial contribution. Thus, the answer to the formulation of the main problem is that the use of AI has a simultaneous relationship with independence, but the meaning of that relationship depends on the way students divide learning responsibilities between themselves and technology.Intensity of use is the most consistent positive predictor. A beta coefficient of 0.246 and a bootstrap interval that did not cross zero indicated that college students who were more active in using AI tended to report higher learning independence after other dimensions were controlled. Regular use can expand the opportunity to get explanations, examples, exercises, alternative ideas, and feedback outside of lecture time.

The literature on chatbots, adaptive learning, and smart tutoring suggests that on-demand support can help students determine their own learning times and paths (Fernández-Herrero, 2024; Kamalov, Calonge, & Gurrib, 2023; Nagaraj et al., 2023). This flexibility is in line with aspects of independence in the form of selecting sources, setting strategies, monitoring progress, and seeking help appropriately (Linnes et al., 2022; Rocha et al., 2022). Students can use AI to repeat concepts they haven't yet understood, look for additional examples, or check for assignment weaknesses before asking for the help of a lecturer. In such situations, AI does not replace students, but expands the resources it can manage. These findings are important because they show that engagement with AI is not always synonymous with dependence. Nonetheless, intensity does not equal quality. Frequent use can support learning when students are still setting goals, examining information, and making decisions on their own, but can be counterproductive if used only to obtain final answers (Breazeal et al., 2024; Liu, Saeed, Abdelrasheed, Shakibaei, & Khafaga, 2022). Therefore, the main implication is not to encourage unlimited frequencies, but to form active, critical, and responsible use habits. The utilization pattern has a positive coefficient, but it is not partially significant. These results do not mean that using AI to search for information, understand material, organize tasks, or improve writing is useless. The literature shows that all of these activities are the main functions of AI in higher education (Agbong-Coates, 2024; Almansour & Alfhaid, 2024). However, the type of activities that are assisted do not necessarily describe the depth of the learning process. Two students can use AI for the same activity, but the first student only asks for criticism of the ideas that have been prepared, while the second student leaves the entire assignment to the system. On the surface, both have similar patterns of utilization, but the level of cognitive responsibility is different. The unique contribution of utilization patterns may also intersect with intensity and dependency when all predictors are included in a single model. These results suggest that subsequent research needs to distinguish formative uses, such as asking for explanations and feedback, from substitutive uses, such as generating final answers without processing. Measurement also needs to include verification behavior, revision, usage disclosure, and the ability to reinterpret AI results. Thus, the insignificant results on the utilization pattern make it clear that the question of 'what is AI used for' needs to be

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Complemented by the question of 'how do students process the results. Ease of use showed no significant partial association with learning independence. AI applications that are easily accessible and operated can reduce technical barriers and increase the likelihood of students using them (Harry & Sayudin, 2023; X. Wang et al., 2024).

However, convenience is a condition of access, not the ability to manage learning. College students can use the app very easily without setting goals, setting a time, checking information, or evaluating results. On the other hand, students who have high self-regulation can still study independently even though the tools used require greater effort. These results are in line with the view that platform quality is only one part of the digital environment, while independence also depends on self-efficacy, motivation, strategy, and learning support (Dai et al., 2024; Zou et al., 2021). The insignificance of convenience also has a practical meaning. Providing access or technical training alone is not enough to increase independence. Colleges need to combine access with the practice of setting goals, examining sources, comparing outputs, and reflecting on the learning process. Convenience can even magnify the risk of superficial use when quality answers seem to be obtainable without adequate effort. Therefore, easy access needs to be balanced with academic demands that maintain students' cognitive engagement. The effectiveness of use was also not significantly related in part with learning independence. These findings distinguish the effectiveness of task completion from the effectiveness of learning. AI can help students find ideas, improve structure and grammar, and complete work faster (Almansour & Alfhaid, 2024; Fernández-Herrero, 2024). However, a neater product does not always show a deeper understanding. Students may find AI effective because the time is reduced or the value of the assignment increases, when it is not necessarily able to explain concepts, defend arguments, or repeat work without assistance. The literature shows that AI assistance can improve momentary performance, but mastery can weaken when support is removed (Allison et al., 2025). This explains why perceived effectiveness is not enough to predict the ability to plan, monitor, and evaluate learning. For program evaluations, the success of AI integration should not only be measured by product satisfaction, speed, or quality. More relevant measures include increased understanding, retention, knowledge transfer, ability to explain processes, and ability to work independently. The contribution of these results is to remind that academic productivity is not synonymous with competency development.

Dependencies point in a negative direction in conventional regression, but bootstrap results need to be read carefully. The conventional p-value of 0.032 and the BCa interval that does not include zero support the indication of a negative relationship, while the bootstrap p of 0.065 indicates its stability is not yet fully strong. These findings are not enough to state causal effects, but are in line with concerns about cognitive offloading. When students become accustomed to handing over search, reasoning, writing, and evaluation to AI, opportunities to practice critical thinking and problem-solving can be reduced (Riess, 2025; J. Wang et al., 2023). Dependency can also reduce motivation to read original sources and examine answers, especially when the system provides quick and convincing results (Cabuquin et al., 2024; Isiaku, Kwala, Sambo, & Isiaku, 2024). Students can produce tasks that look good without understanding the underlying process, so that visible performance is separate from actual competencies. In health education, these risks are important because students must build habits of evidence verification and accountable decision-making (Le Lagadec et al., 2024; Veras et al., 2024). Latitude-cut designs can't ascertain whether dependency decreases independence or if students who are less self-reliant are more likely to rely on AI. Therefore, these results should be positioned as indications that require longitudinal or experimental testing, rather than as final cause-and-effect evidence. The findings of dependency were also related to information quality and academic integrity. Generative models can generate inaccurate, biased, or fictitious references; the risk becomes greater when the output is received without inspection (Guleria, Krishan, Sharma, & Kanchan, 2023; Michel-Villarreal et al., 2023; Shoja et al., 2023).

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Fluent language presentation can make wrong answers seem convincing. In the context of health, the reception of such information can hinder the formation of the habit of assessing evidence. The use of AI to create assignments in their entirety or paraphrase sources without disclosure can also obscure students' competencies and weaken the validity of assessments (Jared & Hanna, 2024; Rumanovská, Lazíková, Takáč, & Stoličná, 2024)(Landers, 2025). Detection devices cannot be the only solution because text can be modified and legitimate use is difficult to distinguish from misuse. Universities need to prioritize AI literacy, transparency, source verification, and process-based assessment design. Lecturers may request a record of the process, draft versions, reasons for selecting sources, reflections on the use of AI, oral presentations, or confirmation of practice. This approach maintains the benefits of AI while ensuring that students continue to do the intellectual work that is the learning goal. The conceptual contribution of this research lies in testing the supporting side and the inhibitory side of AI in a single model. Intensity shows a relatively stable positive relationship, while dependence shows a negative indication; The other three dimensions have no significant partial relationship. The pattern makes it clear that the value of AI education is not determined only by how easy or effective the technology is perceived, but by how intellectual responsibility is shared between students and systems. His empirical contribution is to provide evidence to health college students, contexts that demand information rigor, evidence evaluation, and professional reasoning. Its methodological contribution is the use of multidimensional regression and bootstrap when the residual is formally abnormal. The bootstrap results reinforce the intensity findings while preventing over-inferences about dependencies. For the field of higher education and learning technology, this research supports the framework of productive versus substitute utilization. Productive AI expands access, practice, and feedback while maintaining student control, while substitute AI replaces thought processes and obscures competencies. The framework can be the basis for developing learning instruments, policies, and designs that are more sensitive to the quality of use.

The practical implications of the research cover three levels. At the student level, AI needs to be used to ask for explanations, test understanding, develop alternatives, and receive feedback, along with the obligation to read original sources, check the truth, and take responsibility for the final results. At the lecturer level, assignments need to be designed to assess reasoning and processes, not just products, and be equipped with clear limits on the use of AI. Assessments can utilize graded drafts, reflection journals, oral presentations, case discussions, or practice exams. At the institutional level, guidelines need to regulate the forms of assistance that are allowed, disclosure of use, data protection, information verification, and consequences of violations. AI literacy needs to include bias, hallucinations, privacy, dependencies, and integrity, not just the skills of operating an application. In the health education curriculum, students need to practice comparing AI output with scientific sources, identify unsubstantiated claims, and explain decisions made. Thus, policymakers do not need to choose between a total ban and unlimited use, but directing AI as a tool with humans remaining in charge of academic decisions. This research has several limitations. The cross-section design does not allow the drawing of causal conclusions. Samples come from one institution and are obtained through voluntary response sampling, so participation bias and generalization limitations may occur. The data is self-report and has not been verified through usage logs, duration of access, platform type, prompt quality, task results, or objective capability measurements. The reliability of the ease dimension is 0.636 lower than other dimensions and requires instrument refinement. The model only explains 22.9% of the variation in independence, so other psychological, pedagogical, and institutional factors need to be included in subsequent studies. Residual is not formally abnormal; Bootstrap has been used, but the dependency findings still require replication with a larger sample. Subsequent research is suggested using longitudinal or experimental design, involving multiple institutions, and testing the differences between formative and substitutive uses. A blended approach that combines surveys, interviews, process observations, actual usage data, and competency

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Assessments will provide a more complete explanation of the relationship between AI and learning independence.

4. CONCLUSION

This study shows that the five dimensions of simultaneous use of AI are significantly related to the learning independence of STIKes Muhammadiyah Bojonegoro students, but the model only explains 22.9% of the variation in independence. The intensity of use is a consistent positive predictor, while the pattern of utilization, ease, and effectiveness is not partially significant. Dependencies show indications of negative relationships that should be interpreted with caution because bootstrap results are at the marginal boundary. The main finding of the study is that the educational value of AI is not determined by its use alone, but by the functions it assigns to the technology. AI can support access, exercise, and feedback when students remain in control of their learning goals, verification, and decisions. In contrast, AI has the potential to weaken independence when it replaces reading, reasoning, writing, and evaluating.

This research contributes to the study of learning technology by placing the benefits and risks of AI in a multidimensional model in the context of health higher education. The main implications are the need for AI literacy, clear guidelines for use, information verification, transparency, and process-based assessments. Future research needs to use longitudinal or experimental designs, involve more diverse institutions, and add variables of self-regulation, self-efficacy, motivation, critical thinking, lecturer support, and a culture of integrity. Self-report data also needs to be completed with logs of actual use, types of tasks, prompt characteristics, interviews, observations, and measurement of objective learning outcomes. The instrument of ease and dependency of AI needs to be improved through stronger construct testing. Comparative research between the use of AI as a formative aid and as a substitute for assignments will help explain the conditions when AI strengthens or weakens learning independence.

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