islamentary
Journal Of Islamic Elementary Education

ISLAMENTARY: Journal of Islamic Elementary Education
E-ISSN: 2986-2140
Vol. 4,No.2,August 2026

# THE EFFECT OF THE INTENSITY OF ARTIFICIAL INTELLIGENCE USE IN LEARNING ON STUDENTS' LEARNING

**Hendro Widiatmoko[1], Choli Astutik[2], Mafruhah[3]**

[1,2,3] Universitas PGRI Sumenep
Email: heendrooo123@gmail.com[1], cholilabib@stkippgrisumenep.ac.id[2], mafruhah@stkippgrisumenep.ac.id[3]

Corresponding Author: Hendro Widiatmoko
Article history: Received: July 31, 2026| Revised: August 01, 2026| Available Online: August 08, 2026

**ABSTRACT**

*This study examines how the intensity of Artificial Intelligence (AI) use in learning affects students' learning independence. A quantitative approach was applied using a correlational design and simple linear regression. Data were obtained from 63 seventh-grade students at SMP Negeri 2 Saronggi, Sumenep Regency. The instruments measured AI usage intensity through 5 items and learning independence through 6 items, both using a 1–5 Likert scale. Both measures showed high reliability: α=0.889 for the AI intensity scale and α=0.830 for the learning independence scale, and both were categorized as reliable. According to the Shapiro–Wilk test, the AI scores (p=0.156), learning independence scores (p=0.096), and regression residuals (p=0.750) were normally distributed. Pearson correlation indicated a very strong positive relationship between the two variables (r=0.912; p<0.001). Simple linear regression produced the equation KB=6.434+0.866AI ($R^2$=0.832, F=302.819, p<0.001). In the research sample, AI usage intensity accounted for approximately 83.2% of the variation in learning independence. These results require qualification: Harman's single-factor test found significant common method variance, with a single factor explaining 58.427% of the variance. The observed effect may include inflation caused by similarity in measurement methods and should therefore be treated as an upper bound rather than a pure effect estimate. Even with this limitation, the findings support the alternative hypothesis that greater AI usage intensity has a positive and significant effect on students' learning independence. The findings also highlight the need for AI literacy and educator support to ensure that AI strengthens students' self-regulation in learning rather than replacing it.*

**Keywords:** *Artificial Intelligence, Generative AI, ChatGPT, Usage Intensity; Learning Independence, Self-Directed Learning, Self-Regulated Learning (SRL), Common Method Bias.*

## INTRODUCTION

Students are adopting generative Artificial Intelligence (AI) at an unprecedented rate. In the relatively short period since the emergence of tools such as ChatGPT, their use has expanded from university classrooms to secondary schools, becoming a routine part of everyday learning. Students turn to AI for explanations, feedback, examples, learning resources, and assistance with problem solving. However, this rapid diffusion has not been accompanied by an adequate understanding of how AI affects the learning process itself, creating a gap that requires immediate attention in educational research.

The issue becomes more urgent when considering the other side of the convenience offered by AI. On the one hand, AI has the potential to support learning planning, implementation, monitoring, and reflection; on the other hand, the availability of instant answers and assistance at any time creates a risk known as AI dependency syndrome, a condition in which excessive AI use weakens independent initiative and causes learners to continually rely on AI as an instant solution for completing learning tasks. This risk is closely related to the phenomenon of cognitive offloading, namely the complete delegation of demanding reasoning tasks to AI, causing learners to bypass the phase of productive struggle that is essential for the development of deep cognition. This condition is exacerbated by the illusion of explanatory depth, a cognitive bias in which learners feel that they have deeply understood a concept simply because explanations are easily accessible through AI, even though such understanding may not have been independently internalized. When learners become accustomed to handing over thinking processes, decision-making, and self-evaluation to AI systems, their capacity to learn independently may gradually weaken. This risk is crucial because learning independence is a foundational competence that determines the continuity of learners' development far beyond formal education. If high AI usage intensity is actually associated with lower learning independence, the ongoing phenomenon of mass adoption could have serious long-term consequences for the quality of human resources; however, empirical evidence regarding this relationship remains limited and inconclusive.

The ambivalent impact of AI on learning independence is consistent with the Scaffold-to-Dependency Framework, a conceptual-pedagogical framework that integrates learner independence and learner dependency into a single perspective in the era of generative AI. This framework emphasizes that the impact of AI use in education is determined not merely by technological sophistication, but by pedagogical design, AI literacy, learners' critical engagement, and regulation of the intensity of AI assistance during the learning process. The shift in AI's function from empowering scaffolding to a dependency tool that weakens cognition is determined by the extent to which AI assistance is provided in a controlled manner and gradually reduced as learners' expertise increases. Thus, AI usage intensity—not merely its presence or frequency—becomes a key variable determining whether AI functions as support that strengthens learning independence or instead erodes it.

Several empirical studies have attempted to address this issue through self-directed learning (SDL) and self-regulated learning (SRL) frameworks. Indriani et al. (2024) examined ChatGPT use and learning motivation in relation to SDL among 98 university students. Li and Zhang (2024) also focused on online self-directed learning ability in the context of ChatGPT use. At the school level, Ng, Tan, and Leung (2024) conducted a three-week study involving 74 Secondary 4 students and demonstrated the potential of generative AI chatbots to support SRL. Lee et al. (2024) examined ChatGPT with a guidance mechanism in blended learning and linked it to SRL, higher-order thinking, and knowledge construction. Chiu (2024) developed a classification tool for ChatGPT activities that support psychological needs and SRL phases. Wu and Chiu (2025) showed that the influence of generative AI on SRL is shaped by configurations of learner characteristics and technological affordances. At the synthesis level, Guan et al. (2025), Lan and Zhou (2025), and Banihashem et al. (2025) showed that AI/chatbots can support learning strategies and metacognitive monitoring across various SRL phases, while human agency remains a determining element.

These studies make important contributions, but an unresolved gap remains: existing research tends to focus on how AI features or mechanisms support SDL/SRL phases qualitatively or in short-term contexts, but has not systematically measured how AI usage intensity—distinguished from mere usage frequency—quantitatively affects learners' overall learning independence. Amid the accelerating adoption of AI and the risk of dependency syndrome described in the Scaffold-to-Dependency framework, empirical understanding of the causal relationship between AI usage intensity and learning independence is urgently needed so that learning policies and practices can respond appropriately before negative effects become widespread.

The research question is: does the intensity of Artificial Intelligence use in learning have a positive and significant effect on students' learning independence? Accordingly, the purpose of this study is to analyze the effect of the intensity of Artificial Intelligence use in learning on students' learning independence. The hypotheses are as follows: H0, AI usage intensity has no significant effect on students' learning independence; and Ha, AI usage intensity has a positive and significant effect on students' learning independence..

## LITERATURE REVIEW

AI usage intensity is understood as the degree of regularity, depth, and consistency with which learners use AI in learning activities, distinguishing it from mere usage frequency. Ammari et al. (2025), through a naturalistic analysis of ChatGPT usage logs among university students, showed that AI use patterns in everyday learning vary considerably—in terms of how often, how long, and for what purposes AI is used—so frequency-based measurement alone is insufficient to describe how AI actually functions in the learning process. This finding supports the need for a more multidimensional intensity construct.

In this study, the AI usage intensity construct is measured through five indicators (AI1–AI5), comprising: (1) frequency of AI use in learning activities, (2) duration of interaction with AI, (3) consistency of use over time, (4) purpose or clarity of intended use, and (5) variety of learning activities assisted by AI. These five indicators are designed to capture the qualitative dimensions of AI use, consistent with Achuthan (2025), who emphasizes that the impact of AI on learner autonomy depends greatly on how AI is used, rather than merely on its availability.

Learning independence (learner independence) is a construct closely related to self-directed learning (SDL), learner autonomy, and self-regulated learning (SRL). Devulapalli and Hanneke (2024), in their review of the dimensions of self-directed learning, emphasize that this construct includes learners' ability to take initiative, set goals, select learning strategies and resources, manage time, monitor the learning process, and evaluate learning outcomes independently.

The literature linking AI with SRL/SDL shows a relatively consistent pattern. Azevedo et al. (2022), through the development of the MetaTutor intelligent tutoring system, demonstrated that technology can function as a scaffold supporting SRL when designed to guide rather than replace learners' self-regulation processes. Similarly, Lee et al. (2024) and Chiu (2024) showed that ChatGPT with appropriate guidance mechanisms can support SRL, higher-order thinking, and the fulfillment of learners' psychological needs. However, Guan et al. (2025), Lan and Zhou (2025), and Banihashem et al. (2025) emphasize that these AI roles remain conditional on preserving human agency. Li et al. (2025) reinforce this point through the concept of hybrid human-AI regulated learning, showing that optimal learning regulation emerges from a combination of learner control and AI support rather than the dominance of either party. In other words, learning independence does not automatically increase simply because AI assistance is available; it depends on the extent to which learners remain in control of their own learning processes.

Based on the theoretical review above, this study develops a conceptual framework linking AI usage intensity (variable X) with students' learning independence (variable Y) as follows:

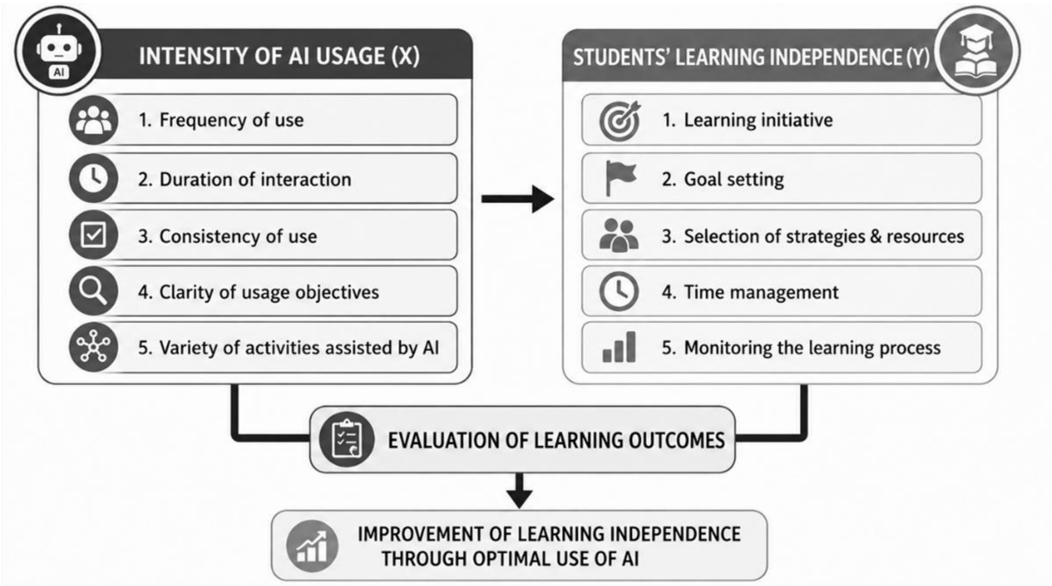

Figure 1. Conceptual Framework

This framework assumes that more intensive and purposeful AI use can expand learners' access to explanations, feedback, learning resources, and metacognitive support, ultimately strengthening learning independence—as demonstrated by Lee et al. (2024), Chiu (2024), and Azevedo et al. (2022) regarding the role of AI as empowering scaffolding. However, Achuthan (2025) cautions that this relationship is not automatically positive, while Li et al. (2025) emphasizes that optimal learning outcomes depend on a balance between AI support and learners' control over the learning process. Therefore, this study tests a positive direction of effect: the higher the intensity of purposeful AI use, the higher students' learning independence, as formulated in the research hypotheses (H0 and Ha).

## METHOD

This study employed a quantitative approach with a cross-sectional correlational design, in which data were collected at a single point in time to examine the relationship between Artificial Intelligence usage intensity and students' learning independence. The population consisted of all seventh-grade students at SMP Negeri 2 Saronggi (NPSN 20529912), a public junior secondary school located on Jalan Tanjung–Saronggi, Kebundadap Timur Village, Saronggi District, Sumenep Regency, East Java Province. The sample was determined using total sampling, involving all students from the three parallel seventh-grade classes at the school—VII/A, VII/B, and VII/C—for a total of 63 respondents.

All students in the three parallel classes were selected so that the data could represent the overall condition of Grade VII rather than only a small subset selected randomly. Nevertheless, because all respondents came from the same school and the same grade level, the research sample was relatively homogeneous in terms of age, cognitive development, and curriculum. Such homogeneity must be acknowledged as a limitation because the relatively restricted score range in a homogeneous sample may increase the observed strength of the correlation between the two research variables, a phenomenon known in research methodology as range restriction. This limitation is an important consideration when interpreting the magnitude of $R^2$ in the Discussion section and provides a basis for recommending that future studies expand the sample to multiple schools and different grade levels to improve the generalizability of the findings.

Data collection used two main questionnaire instruments with a 1–5 Likert scale. The Artificial Intelligence usage intensity variable (X) was measured through five statements (AI1–AI5) covering usage frequency, duration, consistency, purpose of use, and the variety of learning activities assisted by AI, while the learning independence variable (Y) was measured through six statements (KB1–KB6) covering learning initiative, goal setting, selection of learning strategies and resources, time management, process monitoring, and evaluation of learning outcomes. Both instruments were developed by adapting indicators used in previous AI and self-regulated learning literature, particularly the framework of ChatGPT activities mapped onto SRL phases by Chiu (2024) and the learner characteristics and generative AI affordances proposed by Wu and Chiu (2025).

Before being used for data collection, both instruments underwent content validity review through expert judgment to ensure that each statement was relevant to and representative of the construct being measured. Item-total correlation testing (corrected item-total correlation) was also conducted to ensure that each item contributed consistently to the total scale score; all items in both instruments showed adequate item-total coefficients and were therefore retained in the final instruments. Nevertheless, it should be acknowledged as a limitation that a more rigorous construct validity test, such as confirmatory factor analysis, could not be conducted because the sample size of 63 respondents was insufficient to produce stable factor estimates. Thus, the high reliability values of both scales cannot automatically be equated with strong evidence of construct validity, and this constitutes an important direction for future research.

As an additional conceptual note, item AI1, which measures "frequency of AI use," should be considered carefully because it literally overlaps with the notion of frequency that was distinguished from the concept of intensity in the earlier literature review. Therefore, the AI usage intensity construct in this study is more appropriately understood as a composite index combining frequency, duration, consistency, purpose, and variety of use, rather than as a construct completely separate from usage frequency itself.

Data collection was conducted in May 2026 at SMP Negeri 2 Saronggi. The AI usage intensity and learning independence questionnaires were administered face-to-face in class to students in VII/A, VII/B, and VII/C under the supervision of the researcher. Beforehand, a brief explanation of the research purpose and how to complete each statement was provided so that respondents would consistently understand the questions. Before completing the questionnaires, all respondents were informed that participation was voluntary, the data provided would remain confidential and be used only for research purposes, and respondent identities would not be published (anonymity), as an effort to minimize the tendency to provide socially desirable answers rather than genuine responses.

Questionnaire completion took 15–20 minutes for each class and was conducted in the same session for both the AI usage intensity and learning independence measurements to maintain consistent administration conditions across respondents. After data collection, the responses were checked for completeness to ensure that there were no missing data before further statistical analysis.

Because AI usage intensity and learning independence were both measured through self-reports from the same respondents at the same time, there was a potential for common method bias that could make the correlation between variables appear stronger than the actual relationship. To estimate the extent of this potential bias, Harman's single-factor test was conducted by entering all eleven items from both instruments (AI1–AI5 and KB1–KB6) into a single unrotated exploratory factor analysis. If a single factor accounts for a substantial proportion of the variance (commonly above 50%), this indicates that common method variance contributes significantly to the observed correlations.

The analysis showed that the single factor formed explained 58.427% of the total variance, exceeding the commonly used 50% threshold as an indicator of problematic common method variance (Podsakoff et al., 2003). This finding indicates that part of the very strong correlation between AI usage intensity and learning independence ($r=0.912$) may have been influenced by measurement-method bias, given that both variables were measured using self-report instruments from the same respondents at the same time. Therefore, the $R^2=0.832$ reported in the Results section should not be interpreted as a pure estimate of the effect of AI usage intensity on learning independence, but rather as a representation of a relationship that may contain an inflation component resulting from similarity in measurement methods. This limitation is one important reason why future studies should measure the two variables using different data sources (for example, learning independence assessed by teachers rather than solely through student self-reports) or use a time-lagged design in which measurements of AI usage intensity and learning independence are separated by a certain time interval to reduce the risk of correlation inflation caused by common method variance.

The collected data were analyzed through a series of statistical stages arranged sequentially to ensure replicability. The first stage was calculating total scores for each variable, namely the AI usage intensity score (AI_Total) by summing items AI1–AI5 and the learning independence score (KB_Total) by summing items KB1–KB6. Reliability testing using Cronbach's Alpha was then conducted to assess the internal consistency of both scales, along with item-total correlation testing to ensure that each statement contributed consistently to the total score. To detect potential measurement-method bias resulting from simultaneous self-report measurement of both variables, Harman's single-factor test was also conducted as described in Section 3.4.

After instrument testing, descriptive statistical analysis was conducted to obtain an overview of the data, including the mean, standard deviation, minimum, and maximum values of both variables. Before hypothesis testing, normality was assessed using the Shapiro–Wilk test for AI_Total, KB_Total, and regression residuals to ensure that the data met the normality assumption required for parametric statistical analysis. Hypothesis testing was conducted in two stages: Pearson correlation analysis to determine the direction and strength of the relationship between AI usage intensity and learning independence, followed by simple linear regression analysis to determine the magnitude of the effect of AI usage intensity on learning independence and to obtain the regression equation.

To strengthen the reliability of the resulting regression model, several additional assumption tests were conducted, namely the Durbin–Watson test to detect residual autocorrelation, the Breusch–Pagan test to detect heteroscedasticity, and a quadratic component test ($AI^2$) to ensure that the relationship between the two variables was truly linear and did not conceal a more appropriate nonlinear pattern. All tests used a significance level of $\alpha=0.05$ and were conducted using standard, replicable statistical software, namely IBM SPSS Statistics..

# RESULTS AND DISCUSSION

## Descriptive Statistics

| Variable | N | Mean | SD | Min | Max | Mean/Item |
|---|---|---|---|---|---|---|
| AI Usage Intensity | 63 | 18.175 | 3.522 | 10 | 25 | 3.635 |
| Learning Independence | 63 | 22.175 | 3.343 | 14 | 28 | 3.696 |

Table 1. Descriptive Statistics of Research Variables

Based on the category intervals (1.00–1.80 very low; 1.81–2.60 low; 2.61–3.40 moderate; 3.41–4.20 high; 4.21–5.00 very high), the mean item scores for both variables fell into the high category: AI usage intensity was 3.635 and learning independence was 3.696. This finding indicates that respondents in the study generally used AI quite intensively in learning activities and, at the same time, reported a high level of learning independence—a preliminary pattern consistent with the conceptual framework's assumption that purposeful AI use can coexist with learning independence rather than replace it.

## Reliability Test

| Scale | Number of Items | Cronbach's Alpha | Decision |
|---|---|---|---|
| AI Usage Intensity | 5 | 0.889 | Reliable |
| Learning Independence | 6 | 0.830 | Reliable |

Table 2. Reliability Test Results

Both scales met the criteria for internal reliability because their Cronbach's Alpha values exceeded the 0.70 threshold and were even classified as good to very good. This result indicates that the items in each instrument (AI1–AI5 and KB1–KB6) consistently measure the same construct, making the total scores of both variables suitable for further analysis.

## Common Method Bias (CMB) Test

| Test | Result | Threshold | Decision |
|---|---|---|---|
| Harman's Single-Factor Test | Single factor explains 58.427% of variance | <50% | Significant CMV indicated |

Table 3. Common Method Bias Test Results

The results of Harman's single-factor test showed that a single factor formed from the eleven items across both instruments explained 58.427% of the total variance, exceeding the commonly used 50% threshold as an indicator of problematic common method variance (Podsakoff et al., 2003). This finding indicates that part of the strong correlation between AI usage intensity and learning independence may have been influenced by similarity in the measurement method (self-report, the same respondents, and the same measurement time), rather than solely reflecting a substantive relationship between the constructs. The implications of this finding for interpreting the regression results are discussed further in Section 4.7.

## Normality Test

| Variable | W | Sig. | Decision |
|---|---|---|---|
| AI_Total | 0.972 | 0.156 | Normal |
| KB_Total | 0.968 | 0.096 | Normal |
| Residual | 0.987 | 0.750 | Normal |

Table 5. Shapiro–Wilk Normality Test Results

The significance values in all three tests were above 0.05, indicating that the total scores for AI usage intensity and learning independence, as well as the regression model residuals, were normally distributed. With the normality assumption satisfied, the use of Pearson correlation and simple linear regression, which require normally distributed data, was statistically appropriate for the subsequent hypothesis testing.

**Correlation Test**

The Pearson correlation test produced a coefficient of $r=0.912$ ($p<0.001$), indicating a very strong positive relationship between AI usage intensity and students' learning independence. However, because the Harman's single-factor test in Section 4.3 indicated significant common method variance (58.427%), the strength of this correlation cannot be interpreted as purely reflecting a substantive relationship between the constructs; it may contain an inflation component caused by similarity in the measurement method.

**Simple Linear Regression**

| Predictor | B | SE | Beta | t | Sig. |
|---|---|---|---|---|---|
| Constant | 6.434 | 0.921 | – | 6.985 | <0.001 |
| AI_Total | 0.866 | 0.050 | 0.912 | 17.402 | <0.001 |

Table 6. Simple Linear Regression Results

The regression equation obtained was KB_Total = 6.434 + 0.866(AI_Total), with $R=0.912$; $R^2=0.832$; adjusted $R^2=0.830$; $F=302.819$; $p<0.001$. Statistically, this model indicates that 83.2% of the variation in learning independence scores in the sample can be explained by AI usage intensity. Additional assumption tests produced a Durbin–Watson value of 1.858 and a Breusch–Pagan $p=0.429$, indicating no strong evidence of violations of residual independence or heteroscedasticity at the 5% level. The quadratic model showed that the nonlinear $AI^2$ component was not significant ($p\approx0.176$), indicating that simple linear regression was adequate in functional form for describing the relationship between the two variables. Nevertheless, the fulfillment of these statistical assumptions does not eliminate the need to interpret the $R^2=0.832$ magnitude cautiously, given the CMB finding in Section 4.3.

**Discussion**

The correlation coefficient of $r=0.912$ and the coefficient of determination $R^2=0.832$ are exceptionally large for a social science study based on a self-report survey. Before interpreting these findings as strong evidence of the effect of AI usage intensity on learning independence, it is important to first relate them to the Harman's single-factor test results in Section 4.3, which showed that a single factor explained 58.427% of the variance—above the 50% threshold indicating problematic common method variance (CMV). This means that part of the observed strength of the relationship likely does not purely reflect the substantive relationship between the two constructs, but is also influenced by similarity in the measurement method: both variables were measured through self-reports, from the same respondents, at the same time. Therefore, $R^2=0.832$ should be interpreted not as a pure estimate of the effect of AI usage intensity, but as an upper bound of a relationship that likely contains a meaningful methodological inflation component.

Nevertheless, the observed direction of the relationship remains consistent with the findings of Indriani et al. (2024) and Li and Zhang (2024), both of whom reported a positive relationship between ChatGPT use and self-directed learning, as well as Ng et al. (2024), who demonstrated the benefits of generative AI chatbots for SRL among Secondary 4 students. The convergence of findings across studies provides some confidence that the positive relationship between AI usage intensity and learning independence is not merely an artifact, although the effect size reported in this study may be higher than the true substantive effect.

Theoretically, this relationship can be understood through the cyclical self-regulated learning (SRL) framework—forethought, performance, and self-reflection. Chiu (2024) mapped ChatGPT activities onto these SRL phases, while Lee et al. (2024) showed that ChatGPT with a guidance mechanism improves SRL, higher-order thinking, and knowledge construction. Steinert et al. (2023) positioned large language models as providers of formative feedback that supports self-monitoring, while van der Graaf et al. (2022) demonstrated the dynamics between SRL activities and learning outcomes over time. The scaffolding perspective within the zone of proximal development is also relevant, as demonstrated by Azevedo et al. (2022) through MetaTutor and emphasized by Qian et al. (2025) regarding the importance of reliable AI scaffolding. However, Wu and Chiu (2025) caution that SRL outcomes depend on the combination of learner characteristics and technological affordances, not on usage intensity alone—a warning that is increasingly relevant given the CMB findings above.

In addition to common method bias, other alternative explanations should be considered. First, the relationship between AI usage intensity and learning independence may be bidirectional or influenced by unmeasured third variables, such as intrinsic motivation or general self-efficacy, which simultaneously encourage students to use AI more frequently and to learn more independently. Second, sample homogeneity—63 seventh-grade students from the same school—may produce a higher correlation because of the relatively restricted score range (range restriction) compared with a sample drawn from a more diverse population in terms of age, grade level, and school background.

On the other hand, Zheng, Huang, and Chang (2023) showed that ChatGPT can produce untruthful answers, emphasizing that learning independence in the AI era must include the ability to verify information, not merely high usage intensity. Interaction design principles such as Socratic prompting (Chang, 2023), learning-process monitoring through process mining (Fan et al., 2022), and the concept of hybrid human-AI regulated learning (Li et al., 2025) provide directions for positioning AI as a co-regulation partner rather than a replacement for students' self-regulation.

As a final methodological note, this study is correlational and cross-sectional, involving a single homogeneous sample population and—as indicated by the Harman's single-factor test results—contains evidence of common method variance that cannot be ignored. The combination of these limitations means that $R^2=0.832$ should not be interpreted as a precise estimate of causal effect, but rather as an initial indication of a positive relationship that needs to be confirmed through more rigorous designs—for example, by measuring learning independence through teacher assessment rather than solely through student self-reports, applying a time-lagged design to separate the measurement times of the two variables, and expanding the sample to multiple schools and grade levels to reduce the risk of range restriction.:

## CONCLUSION

This study aimed to analyze the effect of Artificial Intelligence (AI) usage intensity in learning on students' learning independence, involving 63 respondents from classes VII/A, VII/B, and VII/C at SMP Negeri 2 Saronggi, Sumenep Regency. The results showed that both research instruments, namely the AI usage intensity scale ($\alpha=0.889$) and the learning independence scale ($\alpha=0.830$), were reliable, and the data for both variables and the regression residuals were normally distributed based on the Shapiro–Wilk test ($p>0.05$ for all three), thereby meeting the requirements for parametric statistical analysis. Pearson correlation showed a very strong positive relationship between AI usage intensity and students' learning independence ($r=0.912$; $p<0.001$), which was further confirmed through simple linear regression with the equation KB_Total=6.434+0.866(AI_Total). The $R^2=0.832$ value indicates that AI usage intensity can explain approximately 83.2% of the variation in learning independence in the sample, while the remaining 16.8% is explained by factors outside the model. Thus, the null hypothesis (H0) is rejected and the alternative hypothesis (Ha) is accepted, meaning that AI usage intensity has a positive and significant effect on students' learning independence. However, because Harman's single-factor test indicated significant common method variance (58.427%), the magnitude of the effect represented by $R^2=0.832$ likely contains an inflation component caused by similarity in the measurement method and should therefore be interpreted as an upper bound of the actual effect rather than a precise estimate of the pure effect. Theoretically, the findings still strengthen the view that AI can function as external scaffolding supporting the phases of self-regulated learning, from planning and monitoring to learning reflection, consistent with recent AI-SRL literature. Nevertheless, because this study used a cross-sectional correlational design with a relatively homogeneous sample population—seventh-grade students from the same school—the results indicate association rather than causation, and generalization to broader student populations, different grade levels, or different forms of AI use should be made cautiously.

## RECOMMENDATIONS

Based on the findings and limitations of this study, future research is recommended to expand the number and distribution of schools or samples in order to improve the generalizability of the findings while reducing the risk of range restriction resulting from sample homogeneity. Future studies should also examine this relationship across different educational levels and subject areas. To address the indication of common method bias identified in this study, future research should measure predictor and outcome variables using different data sources—for example, assessing students' learning independence through teacher ratings rather than relying solely on students' self-reports—or employ a time-lagged design, in which measurements of AI usage intensity and learning independence are separated by a certain time interval to reduce the risk of correlation inflation caused by the similarity of measurement methods. Longitudinal or experimental designs should also be considered to examine the causal direction between AI usage intensity and learning independence, as causal relationships cannot be established through the correlational design used in this study. In addition, the construct of AI usage intensity should be further refined into more detailed indicators, such as frequency, duration, purpose, type of AI, and context of use, while distinguishing it from the quality of AI use, given that how AI is used may be as important as how frequently it is used. Future research is also encouraged to incorporate variables such as AI literacy, self-efficacy, learning motivation, or digital literacy as mediators or moderators to provide a clearer understanding of the mechanisms underlying the observed relationship. Furthermore, more rigorous construct validity testing, such as confirmatory factor analysis, should be conducted using larger samples.

From a practical educational perspective, these findings may serve as a basis for teachers and schools to develop structured guidance for AI use, for example, by encouraging students to verify AI-generated responses and position AI as a tool to support thinking rather than as a substitute for the thinking process itself. Particularly for elementary and secondary school students, as represented by the context of this study, active involvement and supervision from teachers and parents, along with strengthening information-verification literacy, are important because the quality and context of AI use may determine whether the technology strengthens or instead undermines students' learning independence.

**DECLARATIONS**

In the preparation of this article, the authors used an artificial intelligence (AI) tool, namely Claude (Anthropic), to assist with paraphrasing, sentence formulation, language and structural refinement, as well as the preparation of part of the advanced statistical analysis, including the assessment of Common Method Bias using Harman's single-factor test. Nevertheless, all substantive interpretations, methodological decisions, data collection, and final responsibility for the content and conclusions of the article remain entirely with the authors. Accordingly, the use of AI in this article served solely as a writing and analytical support tool and did not replace the authors' roles in designing the research, collecting the data, or drawing scientific conclusions.

This research and article were conducted by three authors from Universitas PGRI Sumenep, with complementary contributions from each author. Hendro Widiatmoko was responsible for the conceptualization of the research, field data collection, statistical data analysis, and preparation of the initial manuscript. Choli Astutik contributed to the development of the research instruments, literature review, and review and refinement of the manuscript. Mafruhah was responsible for research supervision, methodological validation, and review of the final manuscript prior to publication. All authors have read, provided input on, and approved the final version of the article for publication.

This research received no funding or financial support from any grant-awarding institution, whether governmental, commercial, or non-profit. Therefore, all research activities were conducted independently by the authors. The authors further declare that they have no relationship or affiliation with SMP Negeri 2 Saronggi other than its role as the research data collection site. The authors also declare that there are no financial, personal, or professional conflicts of interest that could have influenced the objectivity of the findings reported in this study.

**BIBLIOGRAPHY**

Achuthan, K. (2025). Artificial intelligence and learner autonomy: A meta-analysis of self-regulated and self-directed learning. Frontiers in Education. https://doi.org/10.3389/feduc.2025.1738751

Alfiansyah, A. (2026). The Use of Ai in Islamic Education and Digital Ethics Instruction for Students at Iai Al-Khairat Pamekasan. Molang: Journal Islamic Education, 4(1), 14–21. https://doi.org/10.32806/jm.v4i1.1788

Ammari, et al. (2025). ChatGPT in everyday self-directed learning: Naturalistic logs from undergraduate students.

Annamalai, N., & Nasor, M. (2025). Exploring ChatGPT in education: Unveiling learners' experiences through the lens of self-determination theory. Smart Learning Environments, 12, 59. https://doi.org/10.1186/s40561-025-00393-2

Azevedo, R., Bouchet, F., Duffy, M., Harley, J., Taub, M., Trevors, G., Cloude, E., Dever, D., Wiedbusch, M., Wortha, F., & Brady, A. C. (2022). Lessons learned and future directions of MetaTutor: Multichannel data to scaffold self-regulated learning with an intelligent tutoring system. Frontiers in Psychology. https://doi.org/10.3389/fpsyg.2022.813632

Banihashem, S. K., Bond, M., Bergdahl, N., Khosravi, H., & Noroozi, O. (2025). A systematic mapping review at the intersection of artificial intelligence and self-regulated learning. International Journal of Educational Technology in Higher Education, 22, 50. https://doi.org/10.1186/s41239-025-00548-8

Chang, E. Y. (2023). Prompting large language models with the Socratic method. arXiv:2303.08769.

Chen, A., Le, H., Wei, Y., Zhang, et al. (2024). Learning-by-teaching with ChatGPT: The effect of teachable ChatGPT agent on programming education. arXiv:2412.15226.

Chiu, T. K. F. (2024). A classification tool to foster self-regulated learning with generative artificial intelligence by applying self-determination theory: A case of ChatGPT. Educational Technology Research and Development, 72, 2401–2416. https://doi.org/10.1007/s11423-024-10366-w

Devulapalli, P., & Hanneke, S. (2024). The dimension of self-directed learning. Proceedings of Machine Learning Research, 237, 1–30.

Fan, Y., et al. (2022). Multi-channel data/process mining for self-regulated learning. Metacognition and Learning, 17, 1025–1055. https://doi.org/10.1007/s11409-022-09304-z

Guan, R., Raković, M., Chen, G., & Gašević, D. (2025). How educational chatbots support self-regulated learning? A systematic review of the literature. Education and Information Technologies, 30, 4493–4518. https://doi.org/10.1007/s10639-024-12881-y

He, et al. (2024). The AI companion in education: Analyzing the pedagogical potential of ChatGPT in computer science and engineering. arXiv:2407.05205.

Indriani, W., Nawwaf, M. N., Yundianto, D., Erikha, F., & Khatami, M. (2024). From conversation to competence: The influence of ChatGPT use and learning motivation in improving self-directed learning. Academic Journal of Psychology and Counseling, 5(2), 202–225. https://doi.org/10.22515/ajpc.v5i2.8971

Keech, M., & Goel, A. (2022). Why are some online educational programs successful?: Student cognition and success. Proceedings of the 41st Annual Conference of the Cognitive Science Society.

Lai, J. W. (2024). Adapting self-regulated learning in an age of generative artificial intelligence.

Lan, M., & Zhou, X. (2025). A qualitative systematic review on AI empowered self-regulated learning in higher education. npj Science of Learning, 10, 21. https://doi.org/10.1038/s41539-025-00319-0

Lee, G.-G., & Zhai, X. (2024). Using ChatGPT for science learning: A study on pre-service teachers' lesson planning.

Lee, H.-Y., Chen, P.-H., Wang, W.-S., Huang, Y.-M., & Wu, T.-T. (2024). Empowering ChatGPT with guidance mechanism in blended learning: Effect of self-regulated learning, higher-order thinking skills, and knowledge construction. International Journal of Educational Technology in Higher Education, 21, 16. https://doi.org/10.1186/s41239-024-00447-4

Li, R., & Zhang, G. (2024). The study on the influence of ChatGPT on the online self-directed learning ability of contemporary college students. Journal of Education, Humanities and Social Sciences, 45, 146–151. https://doi.org/10.54097/1cq9yf45

Li, X., Li, T., Yan, L., Li, Y., Zhao, L., Raković, M., Molenaar, I., Gašević, D., & Fan, Y. (2025). Hybrid human-AI regulated learning.
Lo, C. K., Yu, P. L. H., Xu, S., Ng, D. T. K., & Jong, M. S.-Y. (2024). Exploring the application of ChatGPT in ESL/EFL education and related research issues: A systematic review of empirical studies. Smart Learning Environments, 11, 50. https://doi.org/10.1186/s40561-024-00342-5
Mao. (2025). Fostering self-directed growth with generative AI: Toward a new learning framework.
Ng, D. T. K., Tan, C. W., & Leung, J. K. L. (2024). Empowering student self-regulated learning and science education through ChatGPT: A pioneering pilot study. British Journal of Educational Technology, 55(4), 1328–1353. https://doi.org/10.1111/bjet.13454
Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
Qian, K., Liu, S., Li, T., Raković, M., Li, X., Guan, R., Molenaar, I., Nawaz, S., Swiecki, Z., Yan, L., & Gašević, D. (2025). Towards reliable generative AI-driven scaffolding: Reducing hallucinations and enhancing quality in self-regulated learning. arXiv:2508.05929.
Roe, J., & Perkins, M. (2024). Generative AI in self-directed learning: A scoping review.
Sari Nusantara Putri, Alfiansyah Alfiansyah, Implementasi Pembelajaran Adaptif Berbasis Bahasa Alami (Llm) Untuk Meningkatkan Pencapaian Belajar Di Sekolah Dasar , Journal Creativity: Vol. 3 No. 2 (2025): Journal Creativity
Steinert, S., Avila, K. E., Ruzika, S., Kuhn, J., & Küchemann, S. (2023). Harnessing large language models to enhance self-regulated learning via formative feedback. arXiv:2311.13984.
Sui, C.-J., Yen, M.-H., & Chang, C.-Y. (2023). Investigating effects of perceived technology-enhanced environment.
van der Graaf, J., et al. (2022). The dynamics between self-regulated learning and learning outcomes. Metacognition and Learning, 17, 745–771. https://doi.org/10.1007/s11409-022-09308-9
Wu, X.-Y., & Chiu, T. K. F. (2025). Integrating learner characteristics and generative AI affordances to enhance self-regulated learning: A configurational analysis. Journal of New Approaches in Educational Research, 14, 10. https://doi.org/10.1007/s44322-025-00028-x
Zheng, S., Huang, J., & Chang, K. C.-C. (2023). Why does ChatGPT fall short in providing truthful answers? arXiv:2304.10513.