Jurnal Elemen, 12(3), 913-926, July 2026
https:/doi.org/10.29408/jel.v12i3.34820

e- ISSN: 2442 - 4226

AI chatbot usage intensity, academic motivation, and self-efficacy among mathematics education students

Henny Ekana Chrisnawati, Nigel Kris Handoko, Muhammad Ikhsanudin Zaid *, Getut Pramesti

Department of Mathematics Education, Universitas Sebelas Maret, Central Java, Indonesia

* Correspondence: zaidikhsanudinm@student.uns.ac.id
© The Author(s) 2026

Abstract

AI chatbots have become a common source of academic assistance; however, their psychological value for mathematics education students remains unclear when use is considered only in terms of usage intensity. This study examined whether AI chatbot usage intensity is associated with academic motivation and academic self-efficacy among undergraduate mathematics education students. A quantitative correlational design was applied to data from 47 students selected through purposive sampling. Data were collected using an AI chatbot usage intensity measure assessing frequency and duration of use, an academic motivation questionnaire, and an academic self-efficacy questionnaire. Descriptive statistics and Spearman's rho were used because the normality assumption was not fully met. The correlation tests showed no significant association between AI chatbot usage intensity and academic motivation ($\rho = 0.068$, $p = 0.649$) or academic self-efficacy ($\rho = -0.045$, $p = 0.763$). In this sample, more frequent or longer chatbot use was not significantly associated with stronger academic motivation or academic self-efficacy, suggesting that usage frequency and duration alone may not sufficiently explain students' psychological learning outcomes. Future research should examine the purpose, quality, and reflective aspects of chatbot interaction beyond usage frequency and duration.

Keywords: academic motivation; AI chatbot; AI usage intensity; self-efficacy

How to cite: Chrisnawati, H. E., Handoko, N. K., Zaid, M. I., & Pramesti, G. (2026). AI chatbot usage intensity, academic motivation, and self-efficacy among mathematics education students. *Jurnal Elemen, 12*(3), 913-926. https://doi.org/10.29408/jel.v12i3.34820

Received: 10 May 2026 | Revised: 25 July 2026
Accepted: 3 August 2026 | Published: 8 August 2026

Jurnal Elemen is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Introduction

Artificial Intelligence (AI) is increasingly embedded in higher education, changing how students search for explanations, complete academic tasks, and receive learning support. Among the available AI applications, conversational chatbots such as ChatGPT are widely used because they can respond immediately, explain concepts interactively, and provide individualized assistance. Previous studies have linked chatbot-supported learning with student engagement, attitudes, and academic performance, especially when feedback is adaptive and aligned with learning needs (Morell-Mengual et al., 2025; Zawacki-Richter et al., 2019; Ramadan et al., 2024).

Studies in Indonesian higher education have also reported that AI chatbots can make learning activities more efficient and may encourage students to stay engaged with academic work through timely and flexible support (Hadid et al., 2024; Luthfiyyah et al., 2024; Prasetya & Syarif, 2023). However, the increasing availability of AI chatbots does not necessarily indicate that greater usage will automatically produce stronger psychological learning outcomes, as the value of chatbot interaction may depend on how students engage with the technology. Other findings indicate that chatbot use can assist students in understanding concepts and completing academic problem-solving tasks (Dewi et al., 2025; Saifullah et al., 2024).

For mathematics education, the role of AI-supported assistance deserves particular attention because students often face abstract concepts, symbolic representations, and multi-step reasoning. AI tools may help learners revisit explanations, obtain examples, and receive scaffolding during problem solving (Li, 2025; Waziana et al., 2024). In Indonesian university contexts, AI-based support has also been perceived as useful for academic tasks and may relate to students' willingness to engage with challenging content (Wandini et al., 2025).

Academic motivation represents an important psychological factor that influences students' persistence, engagement, and willingness to overcome learning difficulties. Self-Determination Theory (Ryan & Deci, 2000) suggests that motivation is strengthened when students experience autonomy, competence, and relatedness. In the context of AI-supported learning, chatbots may potentially support autonomy by allowing students to explore explanations independently, and support perceptions of competence by providing immediate feedback during learning activities. However, these motivational benefits may depend on whether students actively engage with chatbot-generated information rather than merely use it as a source of instant answers.

Academic self-efficacy is another important factor because it reflects students' belief that they can manage and complete academic demands. From the perspective of Social Cognitive Theory (Bandura, 1997), self-efficacy develops through mastery experiences, vicarious experiences, social persuasion, and emotional states. AI chatbot interactions may contribute to self-efficacy when students receive explanations, feedback, and examples that support successful learning experiences. Nevertheless, excessive reliance on chatbot-generated solutions may limit opportunities for students to develop confidence through independent problem solving. When AI feedback is clear and supportive, students may feel more confident

in approaching mathematical tasks (Nurjannah et al., 2024). Evidence from broader higher education contexts further suggests that AI assistants can support intrinsic motivation and self-efficacy when they are used as learning aids rather than as replacement sources for thinking (Hanshaw et al., 2024).

At the same time, the educational value of AI chatbots is not guaranteed by access alone. If students rely on chatbot responses as shortcuts, the technology may weaken independent reasoning and reduce opportunities for critical thinking (Li & Lyu, 2025). This concern makes it necessary to distinguish between simply using chatbots often and using them in ways that support meaningful learning. Therefore, examining usage indicators in relation to motivation and self-efficacy can help clarify whether the amount of chatbot use is associated with students' psychological learning outcomes.

Previous research has mostly emphasized attitudes, perceptions, adoption intentions, and general experiences with AI chatbots. Fewer studies have focused specifically on usage intensity and its relationship with both academic motivation and academic self-efficacy among Mathematics Education students. This limitation is important because frequent chatbot use may represent different patterns of engagement, ranging from meaningful conceptual exploration to simple answer-seeking behavior, while mathematics learning itself requires persistence, confidence, and reflective problem solving.

Based on this gap, the present study analyzes the relationship between AI chatbot usage intensity and students' academic motivation and academic self-efficacy in a Mathematics Education program. The study focuses on examining whether differences in chatbot usage frequency and duration are associated with students' academic motivation and self-efficacy. The findings are expected to contribute to discussions on responsible AI integration and to inform learning designs that emphasize purposeful and reflective chatbot use.

Methods

This study employed a quantitative correlational design aimed at examining the relationship between the intensity of AI chatbot usage and the academic motivation and self-efficacy of mathematics education students.

The population of this study comprised all active undergraduate students enrolled in the Mathematics Education program at a public university in Surakarta, Indonesia. The sample was selected using purposive sampling, which involves selecting respondents who are considered most likely to provide information relevant to the research objectives (Campbell et al., 2020). Students were eligible to participate if they (1) were actively enrolled in the program, (2) had previously used AI chatbots for learning or academic purposes, and (3) voluntarily agreed to participate in the study. Data were collected between November and December 2025 using an online questionnaire administered via Google Forms. A total of 47 students (23 male and 24 female) met the inclusion criteria and participated in the study. The participants represented various stages of the undergraduate program, ranging from the first to the ninth semester.

Data were collected using a closed-ended questionnaire, where respondents were required to select responses from predefined options. The research instrument consisted of three

constructs: AI chatbot usage intensity, self-efficacy, and academic motivation. The AI chatbot usage intensity instrument was developed and comprised two closed-ended items measuring frequency of use per week and duration of use per day. Each item employed four ordered response categories representing different levels of AI chatbot usage intensity.

The AI chatbot usage intensity instrument was developed as a simple behavioral measure of AI chatbot use in learning activities, focusing on two observable indicators: frequency of AI chatbot use per week and average daily duration of use, which are among the most commonly used behavioral indicators for assessing digital media use in previous studies (Bekalu et al., 2023). Frequency of use was measured using four response categories ranging from once or less per week (1) to seven or more times per week (4). Daily duration of use was likewise measured using four response categories ranging from less than 10 minutes per day (1) to more than 1 hour per day (4). The overall AI chatbot usage intensity score was calculated as the mean of the two indicator scores, resulting in a composite score ranging from 1 to 4, with higher scores indicating greater AI chatbot usage intensity. Frequency and duration were treated as complementary behavioral indicators of AI chatbot use, with frequency reflecting how often students accessed AI chatbots and duration reflecting the amount of time spent using them. Accordingly, the composite score was intended to represent overall behavioral usage intensity rather than a latent psychometric construct. Consequently, internal consistency reliability and item-level validity analyses, which are typically applied to reflective latent constructs, were not performed for this composite behavioral measure.

The self-efficacy instrument was adapted from The Indonesian Academic Self-Efficacy Scale (TIASS) developed by Darmayanti et al. (2024). This instrument employs a four-point Likert scale (1 = strongly disagree to 4 = strongly agree), consistent with the original scale.

The academic motivation instrument was based on the Academic Motivation Scale (AMS) proposed by Vallerand et al. (1992). The original English version was translated into Indonesian and reviewed in consultation with the research supervisor to ensure semantic equivalence, clarity, and appropriateness for the target respondents. The original seven-point Likert scale was modified to a four-point scale (1 = strongly disagree to 4 = strongly agree) to maintain consistency with the self-efficacy instrument administered in the same questionnaire and to provide clearer response categories by reducing ambiguity between adjacent response options. Amotivation items were reverse-scored so that higher total scores consistently reflected higher levels of academic motivation. The adaptation was limited to the response scale format; the original item content, wording, and theoretical dimensions of the Academic Motivation Scale were retained. Further details regarding the variable indicators and number of items are presented in Table 1.

Table 1. Research instrument blueprint

Variable	Indicator	Number of Items	Instrument Type
AI Chatbot Usage Intensity	▪ Frequency of AI chatbot use in learning activities ▪ Duration of AI chatbot use in learning activities	2	Questionnaire
Self-Efficacy (Darmayanti et al., 2024)	▪ Interaction at university ▪ Performance out of class ▪ Performance in class ▪ Managing work, family, and university	20	Questionnaire
Academic Motivation (Vallerand et al., 1992)	▪ Intrinsic motivation – to know ▪ Intrinsic motivation – to accomplish ▪ Intrinsic motivation – to experience stimulation ▪ Extrinsic motivation – identified ▪ Extrinsic motivation – introjected ▪ Extrinsic motivation – external regulation ▪ Amotivation	28	Questionnaire

Item validity was evaluated using the Pearson Product–Moment correlation by correlating individual item scores with total construct scores. An item was regarded as valid when its correlation value was higher than the critical value at the predetermined significance level. To determine the consistency of the instrument, reliability testing was conducted using Cronbach's Alpha, where a coefficient of 0.70 or above indicated acceptable reliability (Taherdoost, 2018).

The data analysis procedure in this research was carried out in two phases, namely descriptive and inferential statistical analyses. Descriptive statistics were used to summarize the characteristics of the study variables, including AI chatbot usage intensity, self-efficacy, and academic motivation. The variables were described using the mean (M), standard deviation (SD), median, interquartile range (IQR), and observed minimum and maximum scores. These descriptive measures were reported to provide information about the central tendency, variability, and distribution of the data.

Inferential statistical analysis began with a normality test to identify whether the data for each variable, AI Chatbot Usage Intensity (X), Self-Efficacy (Y_1), and Academic Motivation (Y_2), were normally distributed. Considering that the number of participants was below 50 (N = 47), the Shapiro–Wilk test was selected for this purpose. The test results indicated that several variables did not meet the assumption of normality. Therefore, the hypothesis testing process was continued using a non-parametric statistical method, specifically Spearman's rho correlation analysis.

Spearman's rho correlation was used to examine the relationships between AI chatbot usage intensity and both academic motivation and self-efficacy. Correlation coefficients, along with their corresponding 95% confidence intervals, were reported to provide information about the strength and precision of the observed relationships. Statistical significance was assessed using two-tailed *p*-values, with $p \leq 0.05$ considered statistically significant. All statistical analyses in this study were performed using IBM SPSS Statistics version 27.

Results

This section reports the statistical findings concerning AI chatbot usage intensity, academic motivation, and academic self-efficacy. The presentation begins with instrument validity and reliability, continues with descriptive distributions of respondents and research variables, and ends with normality and correlation analyses. The complete item validity results are provided in Appendix A.

Item validity analysis showed that every item in the self-efficacy and academic motivation instruments exceeded the required *r* value, indicating that the items were valid for measuring the intended constructs. The item-total correlations ranged from 0.292 to 0.754 for self-efficacy and from 0.308 to 0.812 for academic motivation. Thus, all items were retained for further analysis.

Table 2. Reliability analysis of research constructs

Variable	Cronbach's Alpha	Category
Self-Efficacy	0.862	High
Academic Motivation	0.931	Very High

The reliability results in Table 2 indicate strong internal consistency for both constructs. The self-efficacy scale produced a Cronbach's Alpha of 0.862, while the academic motivation scale reached 0.931. These values show that the instruments were sufficiently consistent for use in the present analysis.

Table 3. Demographic characteristics of the participants

Characteristic	Frequency	Percentage
Gender		
Male	23	48.94%
Female	24	51.06%
Semester		
First	6	12.77%
Third	5	10.64%
Fifth	32	68.09%
Seventh	3	6.38%
Ninth	1	2.13%

Table 3 summarizes the demographic characteristics of the participants. The study included 47 undergraduate students, with a nearly equal distribution of males (48.94%) and females (51.06%). Most participants were in the fifth semester (68.09%), while students from

the first, third, seventh, and ninth semesters accounted for smaller proportions of the sample. This distribution indicates that the participants were primarily drawn from the middle stage of the undergraduate program.

Table 4. Distribution of participants by AI chatbot type

AI Chatbot Type	Frequency	Percentage
ChatGPT	33	70.21%
Gemini	8	17.02%
DeepSeek	3	6.38%
Others	3	6.38%
Total	47	100%

As presented in Table 4, ChatGPT was the most frequently used AI chatbot among the participants (70.21%), followed by Gemini (17.02%). DeepSeek and other chatbots were used by relatively few students (6.38% each), indicating that ChatGPT was the primary AI chatbot platform in this study.

Table 5. Descriptive statistics of the research variables

Variable	M	SD	Median	IQR	[Min, Max]
AI Chatbot Usage Intensity	2.85	0.74	3.00	1.00	[1.00, 4.00]
Self-Efficacy	2.89	0.35	2.90	0.40	[1.80, 3.75]
Academic Motivation	3.10	0.41	3.14	0.47	[1.64, 3.82]

Note. *M* = mean; *SD* = standard deviation; IQR = interquartile range; [Min, Max] = observed minimum and maximum scores.

The descriptive statistics presented in Table 5 indicate that AI chatbot usage intensity had a mean score of 2.85 (*SD* = 0.74), with a median of 3.00 and an interquartile range (IQR) of 1.00. The observed scores ranged from 1.00 to 4.00, suggesting considerable variation in students' reported chatbot usage intensity. Self-efficacy showed a mean score of 2.89 (*SD* = 0.35), with a median of 2.90 and an IQR of 0.40. The relatively small standard deviation and interquartile range indicate that students' self-efficacy scores were fairly consistent across the sample. Academic motivation had the highest mean score among the three variables (*M* = 3.10, *SD* = 0.41), with a median of 3.14 and an IQR of 0.47. The distribution of scores suggests that students generally reported relatively high levels of academic motivation, although some variability was still observed.

Table 6. Normality test results

Variable	*p*	Interpretation
AI Chatbot Usage Intensity	0.012	Not Normally Distributed
Self-Efficacy	0.423	Normally Distributed
Academic Motivation	0.016	Not Normally Distributed

Table 6 displays the Shapiro-Wilk normality results. Self-efficacy was normally distributed ($p = 0.423$), whereas AI chatbot usage intensity ($p = 0.012$) and academic motivation

(p = 0.016) were not normally distributed. Because the assumption of normality was not fully met, Spearman's rho was selected for the correlation analysis.

Table 7. Correlation analysis using Spearman's rho

Variables	ρ	95% CI	*p*
AI Chatbot Usage Intensity – Self-Efficacy	-0.045	[-0.336, 0.253]	0.763
AI Chatbot Usage Intensity – Academic Motivation	0.068	[-0.232, 0.356]	0.649

Note. ρ = Spearman's rho correlation coefficient; CI = 95% confidence interval; p = two-tailed significance level.

The results of the Spearman's rho correlation analysis presented in Table 7 indicated no statistically significant associations between AI chatbot usage intensity and either psychological variable. The correlation with self-efficacy was very weak and negative (ρ = -0.045, 95% CI [-0.336, 0.253], p = 0.763), whereas the correlation with academic motivation was very weak and positive (ρ = 0.068, 95% CI [-0.232, 0.356], p = 0.649). In both cases, the 95% confidence intervals included zero, indicating that the observed data were consistent with a range of possible population correlations, including no association. Given the relatively small sample size (N = 47), the width of these confidence intervals indicates considerable uncertainty in the estimation of the population correlations. Although the observed correlations were close to zero, the intervals included both negative and positive values, meaning that a weak association in either direction cannot be ruled out.

Discussion

The findings indicate that AI chatbot usage intensity was not significantly associated with academic motivation or academic self-efficacy among Mathematics Education students. Although chatbots, particularly ChatGPT, were used by respondents with varying levels of intensity, the amount of use did not correspond to stronger academic motivation or higher academic self-efficacy. This result suggests that chatbot usage intensity alone may not sufficiently explain differences in students' psychological learning outcomes. This interpretation is consistent with previous findings indicating that AI integration in education involves broader changes in learning practices beyond simple technology exposure (Kharis et al., 2024).

Several methodological factors may also help explain these non-significant findings. The non-significant results may partly reflect limited statistical power, given the relatively small sample size (N = 47), which may reduce the ability to detect weak associations. In addition, the sample was drawn exclusively from undergraduate students in a single Mathematics Education program, which may have limited the variability in both chatbot usage patterns and psychological outcomes; students within the same academic program may experience relatively similar learning environments and academic demands, which could reduce variability in the measured variables.

The measurement approach used for AI chatbot usage intensity may also have contributed to the null findings. Because this construct was captured through only two items—frequency and duration of use—it may not fully capture other relevant aspects of chatbot engagement, such as the purpose of use, the quality of interaction, reflective engagement, or students' dependence on AI-generated responses. Moreover, the limited number of indicators may introduce measurement constraints, as frequency and duration represent the quantity of chatbot use but may not fully reflect the broader characteristics of students' interactions with AI chatbots. Similarly, academic motivation was represented as a single aggregated score combining intrinsic motivation, extrinsic motivation, and amotivation; this aggregation may have obscured associations that exist at the level of specific motivational dimensions, since these components can theoretically relate to chatbot use in different or even opposing directions.

One possible explanation is that intensity reflects quantity of use rather than the quality of learning engagement. Frequency and duration show how often students access chatbots, but they do not reveal whether students use the responses to compare ideas, check reasoning, ask follow-up questions, or reflect on mathematical concepts. Thus, motivational outcomes may also be related to how chatbot interactions are structured pedagogically rather than to usage frequency alone (Septiyanti et al., 2024). However, this interpretation was not directly tested in the present study because the quality and structure of students' chatbot interactions were not measured.

This interpretation is consistent with a scoping review showing that chatbots may support motivation, but their effects differ across learning settings and implementation designs (Huang et al., 2025). In the present study, AI chatbot usage intensity, as measured through frequency and duration, was not significantly associated with academic motivation or academic self-efficacy. This finding suggests that routine access to chatbots should not automatically be regarded as equivalent to meaningful learning support.

Research on students' attitudes toward generative AI has also shown that positive perceptions may be shaped by convenience and ease of access, but such perceptions do not necessarily produce deeper psychological outcomes (Morell-Mengual et al., 2025). In other words, students may value chatbots because they are fast and accessible while still relying on other sources, such as prior knowledge, classroom support, or personal learning habits, to build motivation and confidence.

The weak relationship between usage intensity and the two psychological variables may also be explained by differences in learner characteristics. Students who already have higher curiosity, confidence, or digital competence may interact with AI tools differently from students who use them only for quick task completion (Schutte & Li, 2025). However, this explanation is drawn from the broader literature rather than directly tested in the present study, since learner characteristics such as curiosity and digital competence were not measured here. Therefore, usage intensity alone may not fully capture the cognitive and affective processes involved when students work with AI chatbots.

These findings are not necessarily inconsistent with studies showing that self-efficacy, effort expectancy, and performance expectancy can predict interest in AI-assisted mathematics learning (Li, 2025). Rather, they suggest that the number of interactions is not equivalent to

productive interaction. A student may use a chatbot frequently but still engage passively, while another student may use it less often but in a more reflective and problem-oriented manner.

The findings provide practical implications for mathematics education. Lecturers may consider designing activities that encourage students to evaluate AI responses, explain their reasoning, revise prompts, and connect chatbot feedback with mathematical concepts. Guided and reflective chatbot use of this kind may represent a promising direction for future experimental research, rather than a confirmed outcome of the present correlational study (Jayaputri, 2024).

Future studies should move beyond frequency and duration as the main indicators of chatbot use. Further research could examine the purposes of chatbot use, prompt quality, response evaluation, metacognitive engagement, and classroom guidance. These dimensions may provide a clearer explanation of when and how AI chatbots contribute to students' motivation and self-efficacy in mathematics education.

Conclusion

AI chatbot usage intensity was not significantly related to academic motivation or academic self-efficacy among Mathematics Education students. Although respondents reported varying levels of AI chatbot use, greater frequency and longer duration of use were not accompanied by stronger motivation or higher confidence in completing academic tasks.

No significant association was found in this sample, suggesting that usage frequency and duration alone may not sufficiently explain students' psychological learning outcomes. This finding should not be interpreted as evidence that AI chatbots lack educational value; rather, it reflects the scope of the present study, which examined quantitative indicators of chatbot use without capturing the purpose, quality, or reflective depth of students' interactions with the tool.

This study is limited by its relatively small sample size ($N = 47$), correlational design, and measurement of chatbot usage based primarily on frequency and duration. Future research should examine additional dimensions of chatbot engagement, including usage purposes, interaction quality, learning strategies, and reflective engagement, to better understand how AI chatbot use relates to students' motivation and self-efficacy.

Acknowledgment

We are grateful to Universitas Sebelas Maret, especially the Research and Community Service Institute (LPPM UNS), for their financial support through the PKGR-UNS research scheme. We also thank the Department of Mathematics Education and all participants for their cooperation and contributions to the completion of this research.

Declarations

Conflicts of Interest	:	We declare no conflict of interest related to this manuscript.
Generative AI Statement	:	AI Used for Limited, Non-Substantive Support: Generative AI tools, such as ChatGPT, were used only to assist with language editing and minor phrasing enhancements. All conceptualization, analysis, and scholarly content were independently developed and verified by the authors.
Funding Statement	:	This work was supported by Universitas Sebelas Maret through the Research and Community Service Institute (LPPM UNS) under the PKGR-UNS research scheme [Grant Number 462/UN27.22/PT.01.03/2026].
Author Contributions	:	**Henny Ekana Chrisnawati:** Funding acquisition; **Nigel Kris Handoko:** Conceptualization, methodology, formal analysis, data curation, original draft preparation, and visualization**;** **Muhammad Ikhsanudin Zaid:** Conceptualization, methodology, investigation, original draft preparation, and project administration; **Getut Pramesti**: Validation, review and editing, and supervision.

References

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.

Bekalu, M. A., Sato, T., & Viswanath, K. (2023). Conceptualizing and measuring social media use in health and well-being studies: Systematic review. *Journal of Medical Internet Research*, *25*, e43191. https://doi.org/10.2196/43191

Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: Complex or simple? Research case examples. *Journal of Research in Nursing, 25*(8), 652–661. https://doi.org/10.1177/1744987120927206

Darmayanti, K. K. H., Meyrinda, J., Anggraini, E., Utami, A. N., Martha, A. S. D., Faizah, L., Maulina, D., & Seniati, A. N. L. (2024). Testing psychometric property on the Indonesian Academic Self-Efficacy Scale (TIASS). *Jurnal Psikologi, 23*(2), 154–175. https://doi.org/10.14710/jp.23.2.154-175

Dewi Purnama Sari, Alinurdin, & Salwa Alifah, R. P. (2025). Hubungan ChatGPT dan motivasi belajar dengan kemampuan pemecahan masalah matematis siswa [The relationship between ChatGPT and learning motivation and students' mathematical problem-solving skills]. *Jurnal Pancasila dan Kewarganegaraan (JUPANK), 5*(1), 665–672. https://doi.org/10.36085/jupank.v5i1.8066

Hadid, S., Ramadhani, U., Dian Suari, S., & Eka Putri, A. G. (2024). Analisis dampak penggunaan chatbot AI dalam pembelajaran di kalangan mahasiswa PGSD Universitas Jambi [An analysis of the impact of AI chatbots on learning among elementary education students at the University of Jambi]. *Jurnal Pendidikan Terapan, 2*(3), 160–166. https://doi.org/10.61255/jupiter.v2i3.461

Hanshaw, G., Vance, J., & Brewer, C. (2024). Exploring the effectiveness of AI course assistants on the student learning experience. *Open Praxis, 16*(4), 627–644. https://doi.org/10.55982/openpraxis.16.4.719

Huang, W., Jiang, J., King, R. B., & Fryer, L. K. (2025). Chatbots and student motivation: A scoping review. *International Journal of Educational Technology in Higher Education, 22*(1), 24. https://doi.org/10.1186/s41239-025-00524-2

Jayaputri, H. E. (2024). ChatGPT in action: Unraveling its impact on student motivation in English language learning. *Scope: Journal of English Language Teaching, 8*(2), 448. https://doi.org/10.30998/scope.v8i2.22375

Kharis, M., Ediyanto, Wijaya, D., Yafie, E., & Waluyo, B. (2024). The impact of AI usage on transforming student learning culture in Indonesia in alignment with SDG 4. *Journal of Ecohumanism, 3*(8), 1651–1661. https://doi.org/10.62754/joe.v3i8.4845

Li, C., & Lyu, B. (2025). Investigating the motivational and knowledge affordances of conversational AI using induction, concretization, and exemplification in math learning. *British Journal of Educational Technology, 56*(5), 1814–1841. https://doi.org/10.1111/bjet.13612

Li, K. (2025). Factors influencing learners' learning interest when using AI chatbot–assisted math learning in higher education. *Frontiers in Psychology, 16*, 1716913. https://doi.org/10.3389/fpsyg.2025.1716913

Luthfiyyah, K., Zhafira, L., Nurani, S., & Giwangsa, S. F. (2024). Analisis peran artificial intelligence (AI): ChatGPT dalam perkuliahan di kalangan mahasiswa PGSD Universitas Pendidikan Indonesia [Analysis of the role of artificial intelligence (AI): ChatGPT in classroom instruction among elementary education (PGSD) students at the Indonesia University of Education]. *Jurnal Pendidikan Tambusai, 8*(1), 5282–5290. https://jptam.org/index.php/jptam/article/view/13221

Morell-Mengual, V., Fernández-García, O., Berenguer, C., Ortega-Barón, J., Gil-Llario, M. D., & Estruch-García, V. (2025). Characteristics, motivations, and attitudes of students using ChatGPT and other language model-based chatbots in higher education. *Education and Information Technologies, 30*(15), 22257–22274. https://doi.org/10.1007/s10639-025-13650-1

Nurjannah, N., Heriyanti, A., Irmayanti, & Khatimah, H. (2024). Analisis pengaruh penggunaan ChatGPT terhadap kepercayaan diri dan keyakinan mahasiswa dalam memecahkan masalah matematika [An analysis of the effect of ChatGPT use on college students' self-confidence and confidence in solving math problems]. *Jurnal MathEdu (Mathematic Education Journal), 7*(3), 149–155. https://doi.org/10.37081/mathedu.v7i3.6069

Prasetya, R. E., & Syarif, A. (2023). ChatGPT as a tool for language development: Investigating its impact on proficiency and self-evaluation accuracy in Indonesian higher education. *Voices of English Language Education Society, 7*(3), 402–415. https://doi.org/10.29408/veles.v7i3.19303

Ramadan, F., Sari, P. K., & Murti, Y. R. (2024). Examining students' motivation to continue using AI-chatbot for academic assignment. *Jurnal Sistem Informasi, 20*(2), 18–31. https://doi.org/10.21609/jsi.v20i2.1417

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Saifullah, S., Yawan, H., Syafitri, N., & Nurhaliza, S. (2024). Integrating AI chatbot into learning management system: Enhancing student engagement and learning outcomes. *Dharmas Education Journal, 5*(2), 1346–1359. https://doi.org/10.56667/dejournal.v5i2.1605

Schutte, N. S., & Li, H. (2025). The role of self-efficacy and curiosity in student use of artificial intelligence (AI). *International Journal of Educational Technology in Higher Education, 22*(1), 73. https://doi.org/10.1186/s41239-025-00574-6

Septiyanti, N. D., Luthfi, M. I., & Darmawansah, D. (2024). Effect of chatbot-assisted learning on students' learning motivation and its pedagogical approaches. *Khazanah Informatika: Jurnal Ilmu Komputer dan Informatika, 10*(1), 69–77. https://doi.org/10.23917/khif.v10i1.4246

Taherdoost, H. (2018). Validity and reliability of the research instrument: How to test the validation of a questionnaire/survey in a research. *International Journal of Academic Research in Management, 5*(3), 28–36. https://doi.org/10.2139/ssrn.3205040

Vallerand, R. J., Pelletier, L. G., Blais, M. R., Brière, N. M., Senécal, C., & Vallières, E. F. (1992). The Academic Motivation Scale: A measure of intrinsic, extrinsic, and amotivation in education. *Educational and Psychological Measurement, 52*(4), 1003–1017. https://doi.org/10.1177/0013164492052004025

Wandini, W. T., Nugroho, D. R., Ulya, E. D., & Mulyono, M. (2025). Pengaruh penggunaan artificial intelligence ChatGPT dalam penyelesaian tugas terhadap motivasi belajar mahasiswa [The effect of using ChatGPT artificial intelligence to complete assignments on students' motivation to learn]. *RIGGS: Journal of Artificial Intelligence and Digital Business, 4*(4), 7145–7151. https://doi.org/10.31004/riggs.v4i4.4688

Waziana, W., Andewi, W., Hastomo, T., & Hasbi, M. (2024). Students' perceptions about the impact of AI chatbots on their vocabulary and grammar in EFL writing. *Register Journal, 17*(2), 352–382. https://doi.org/10.18326/register.v17i2.352-382

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Appendix

Appendix A. Instrument Item Validity

Variable	Item	*r*-value	Variable	Item	*r*-value
Self-Efficacy	SE_01	0.457	Academic Motivation	AM_01	0.311
	SE_02	0.494		AM_02	0.791
	SE_03	0.611		AM_03	0.698
	SE_04	0.292		AM_04	0.642
	SE_05	0.487		AM_05	0.489
	SE_06	0.478		AM_06	0.745
	SE_07	0.442		AM_07	0.695
	SE_08	0.629		AM_08	0.474
	SE_09	0.303		AM_09	0.746
	SE_10	0.591		AM_10	0.555
	SE_11	0.629		AM_11	0.526
	SE_12	0.748		AM_12	0.308
	SE_13	0.494		AM_13	0.697
	SE_14	0.637		AM_14	0.711
	SE_15	0.754		AM_15	0.656
	SE_16	0.626		AM_16	0.812
	SE_17	0.570		AM_17	0.663
	SE_18	0.545		AM_18	0.332
	SE_19	0.359		AM_19	0.601
	SE_20	0.315		AM_20	0.660
				AM_21	0.410
				AM_22	0.438
				AM_23	0.676
				AM_24	0.746
				AM_25	0.545
				AM_26	0.656
				AM_27	0.739
				AM_28	0.783

Note. All items met the validity criteria ($r \geq 0.287$).