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AI Chatbot Use in Higher Education: A Life-Course Perspective on Student Engagement and Cognitive Learning Outcomes

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ABSTRACT

Purpose - The increasing use of artificial intelligence (AI) chatbots in higher education has reshaped how students engage with learning activities and develop cognitive skills. From a life-course education perspective, higher education represents a critical stage in early adulthood where learning experiences may influence long-term learning habits and readiness for lifelong learning. However, empirical studies integrating chatbot usage intensity, AI effectiveness, and student engagement within a single explanatory model remain limited, particularly in developing country contexts. This study examines the effects of AI chatbot usage intensity and perceived AI effectiveness on students' cognitive learning outcomes, with student engagement positioned as a mediating mechanism.

Design/methods/approach - A quantitative cross-sectional survey was conducted involving 88 undergraduate students who had experience using AI chatbots for academic purposes. Data were collected using a validated questionnaire and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test direct and indirect relationships among the constructs.

Findings - The results indicate that both chatbot usage intensity and AI effectiveness have significant positive effects on cognitive learning outcomes. These variables also significantly enhance student engagement, which in turn positively influences cognitive learning outcomes. Mediation analysis reveals that student engagement significantly mediates the relationship between AI effectiveness and cognitive learning outcomes, but not between chatbot usage intensity and cognitive learning outcomes, highlighting the dominant role of interaction quality over frequency of use.

Research implications/limitations - The findings underscore the importance of designing AI-supported learning environments that prioritize pedagogical effectiveness and meaningful engagement rather than mere intensity of use. The cross-sectional design and reliance on self-reported data limit causal inference and generalizability.

Originality/value - This study contributes to artificial intelligence in education research by integrating engagement as a mediating mechanism within a life-course framework, offering insights into how AI chatbot use during early adulthood may support sustainable cognitive development and lifelong learning readiness.

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INTRODUCTION

Artificial Intelligence (AI) has developed rapidly and has had a major impact on various sectors, including higher education. AI-based technologies, such as chatbots, are used to provide personalized learning, give instant feedback, and improve the efficiency of the learning process (Rifky, 2024). The (OECD, 2020) emphasizes that AI has great potential to strengthen personalized learning through adaptive support and rapid responses to learners' needs. This development positions AI as a strategic component in global education transformation and calls for scientific analysis of how the technology can be used effectively in the context of learning.

In Indonesia, the use of AI is becoming more widespread as digital transformation develops in various sectors, including education, health, and industry (Wibowo & Ariany, 2024). Students are the group that most frequently uses AI to search for information, understand material, and complete academic assignments (Yani, 2024). However, the implementation of AI in higher education still faces challenges, such as unequal access to technology, uneven digital literacy, and variations in the quality of AI systems used in learning. This shows that the success of AI-based learning is not only determined by the availability of technology, but also by the quality of interaction between students and AI systems.

Within a theoretical framework, the use of AI in learning can be linked to the Social Constructivism theory developed by Vygotsky in 1978. Chatbots can function as scaffolding tools that provide adaptive feedback and help students understand concepts gradually. (OECD, 2020). Therefore, variables such as Chatbot Usage Intensity, Effectiveness of AI, Engagement, and Cognitive Learning Outcomes are relevant to study in order to understand how AI affects the learning process of students.

Previous studies have shown that the effectiveness of AI is related to the quality of explanations and the accuracy of feedback provided by the system (Mayasari et al., 2023). Interaction with chatbots can also improve students' analytical and logical abilities (Firjatullah et al., 2025). In addition, repeated use of chatbots can increase learning efficiency and independence (Sahabuddin et al., 2025). The quality of AI responses is one of the important factors that influence student engagement levels during the learning process (Zhang et al., 2023). These findings indicate that the intensity of chatbot use and the effectiveness of AI have the potential to directly or indirectly impact student engagement and learning outcomes.

Although the use of chatbots in higher education is becoming increasingly widespread, empirical literature examining the relationship between chatbot usage intensity, AI effectiveness, engagement, and cognitive learning outcomes is still limited in the Indonesian context. Many previous studies have only highlighted one aspect, such as AI effectiveness or chatbot usage, without testing how these two variables interact in a structural model. In addition, studies on the role of engagement as a mediator are still rare and show varying results. These limitations indicate the need for research that comprehensively tests the direct and indirect relationships between these variables in a single analytical model.

Based on these gaps, this study aims to analyze the influence of Chatbot Usage Intensity and Effectiveness of AI on Cognitive Learning Outcomes, both directly and through Engagement as a mediating variable. The PLS-SEM approach is used to evaluate the relationship between variables and provide empirical understanding of how students interact with AI chatbots and how the quality of feedback and intensity of use contribute to improving cognitive learning outcomes.

RQ 1: Do Chatbot Usage Intensity and Effectiveness of AI have a positive and significant effect on Cognitive Learning Outcomes?

RQ 2: Do Chatbot Usage Intensity and Effectiveness of AI have a positive and significant effect on Engagement?
RQ 3: Does Engagement have a positive and significant effect on Cognitive Learning Outcomes?
RQ 4: Does Engagement mediate the relationship between Chatbot Usage Intensity AI and Effectiveness of AI on Cognitive Learning Outcomes?

METHOD

This study uses a quantitative approach with a cross-sectional survey design to evaluate the predictive relationship between constructs related to the use of artificial intelligence-based chatbots in the context of higher education (Creswell & Creswell, 2018). This design was chosen because it allows researchers to observe research variables at a single point in time, thereby providing a comprehensive empirical picture without the need for experimental treatment. In this study, the model tested involved the direct and indirect effects between Chatbot Usage Intensity, Effectiveness of AI, Engagement, and Cognitive Learning Outcomes, all of which are latent variables that require a structural analysis approach. This design approach is commonly used in modern educational research focusing on the use of digital technology and artificial intelligence.

The research participants consisted of 88 active students from Makassar State University who had experience using AI chatbots such as ChatGPT in academic activities, whether to understand material, complete assignments, or explore new concepts. This number of participants was considered learning process. Given that the population was quite large and not all students had direct experience with AI, the researchers used purposive sampling to select respondents based on specific criteria, namely students who had interacted with AI chatbots in an academic context. This technique is considered appropriate because it allows for the selection of individuals who are truly relevant to the research phenomenon, so that the data obtained is more representative of the research objectives (Hossan et al., 2024). In addition, this technique is also effective in technology-based educational research where user experience variation greatly determines data quality.

The research instrument is a structured questionnaire designed to measure four main constructs: Chatbot Usage Intensity (CUI), Effectiveness of AI (EOA), Engagement (E), and Cognitive Learning Outcomes (CLO). Each construct consists of five statement items compiled based on theoretical indicators and measured using a five-point Likert scale, which is the most common approach for measuring perceptions, attitudes, and experiences in quantitative research (Koo & Yang, 2025). The questionnaire was developed following the stages of scientific instrument development, including construct identification, indicator formulation, statement item formulation, and content validation using the Index of Item Congruence (IOC) method conducted by experts in the fields of education and technology (Ismail & Zubairi, 2021).

The instrument validation process also considers the principles of item clarity, concept relevance, and consistency between indicators and statements, as explained by (Kishore et al., 2021), who emphasize that the quality of an instrument is determined by the accuracy of the indicators' representation of the research construct. In addition, the principles put forward by (Suasapha, 2020) were also used to ensure that each item was free from ambiguity, easy for respondents to understand, and appropriate to the context of the population, particularly the students who were the subjects of the study. Based on the experts' assessment, all items on the questionnaire met the concept validity criteria and were declared valid for use in data collection.

Table 1. Research Instruments

No	Variable	Statement	References
1	Chatbot Usage Intensity (CUI)	1-5	(Capinding, 2024)
2	Effectiveness Of AI (EOA)	6-10	(Nemt-allah et al., 2024)
3	Engagement (E)	11-15	(Capinding, 2024)
4	Cognitive Learning Outcomes (CLO)	16-20	(Geroche & Guay, 2024)

This research was conducted through several systematic stages. The initial stage included identifying the problem, collecting literature, and developing a conceptual framework that explained the relationship between the research variables. Next, the researchers developed instruments, conducted content validation, and adjusted the wording of the items so that they could be easily understood by students from various backgrounds. After the instruments were validated by experts, the questionnaire was distributed via Google Forms, which was chosen for its efficiency, accessibility, and ability to collect large amounts of data in a relatively short time. The data obtained was then checked for completeness, and only responses that were complete, consistent, and met the research criteria were included in the analysis.

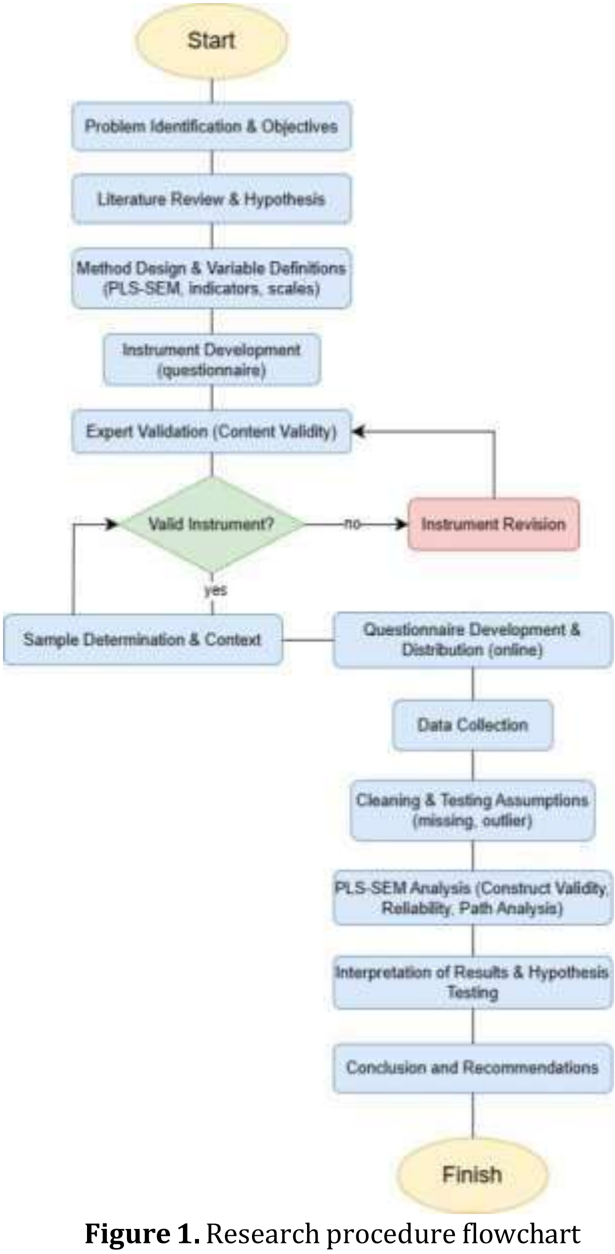

Figure 1. Research procedure flowchart

Data analysis was conducted in two main stages, namely descriptive analysis and inferential analysis using Jamovi and SmartPLS software. Descriptive analysis was used to describe the characteristics of the respondents and the distribution patterns of the data for each research variable. This procedure included identifying the central tendency and dispersion of the data, examining extreme data, and assessing the suitability of the data before proceeding to the advanced analysis stage (Kotronoulas et al., 2023). This stage was carried out using Jamovi, which provides a user-friendly interface and supports statistical analysis needs in the context of social and educational research (Ibáñez-López et al., 2024; Şahin & Aybek, 2020).
The second stage is inferential analysis, which aims to test the relationships between latent variables according to the conceptual model of the study. The initial analysis was conducted by examining the

correlations between constructs using Jamovi to understand the basic relationship trends. Next, structural model testing is performed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method through the SmartPLS application, which was chosen for its ability to handle complex relationships, moderate sample sizes, and mediation roles in a single model simultaneously (Hair et al., 2017). Analysis in PLS-SEM includes evaluation of the measurement model (outer model) and structural model (inner model).

Outer model evaluation was conducted to ensure that the indicators used were able to represent the construct well. This procedure included testing convergent validity through outer loading values and Average Variance Extracted (AVE), construct reliability through Composite Reliability and Cronbach's Alpha, and discriminant validity through the Fornell-Larcker criteria and Heterotrait-Monotrait Ratio (HTMT). Values that meet the recommended thresholds indicate that the construct has good measurement quality (Franke & Sarstedt, 2019; Hair Jr. et al., 2021; Sarstedt et al., 2021). In this study, indicators that did not meet the convergent validity criteria were removed to maintain model integrity, as recommended (Hair et al., 2017).

After the measurement model meets the criteria, the analysis continues on the inner model to test the strength and direction of the relationship between latent variables. The evaluation is carried out through path coefficient values, t-statistics, and p-values generated through the bootstrapping technique, a resampling procedure that provides stable estimates in moderate sample sizes (Streukens & Leroi-Werelds, 2016). The interpretation of relationships was based on statistical significance and the magnitude of influence according to modern PLS-SEM guidelines, where higher path coefficient values indicate a stronger influence (Benitez et al., 2019; Hair Jr. et al., 2021). The results of the evaluation at this stage were used to determine whether the research hypotheses were empirically supported.

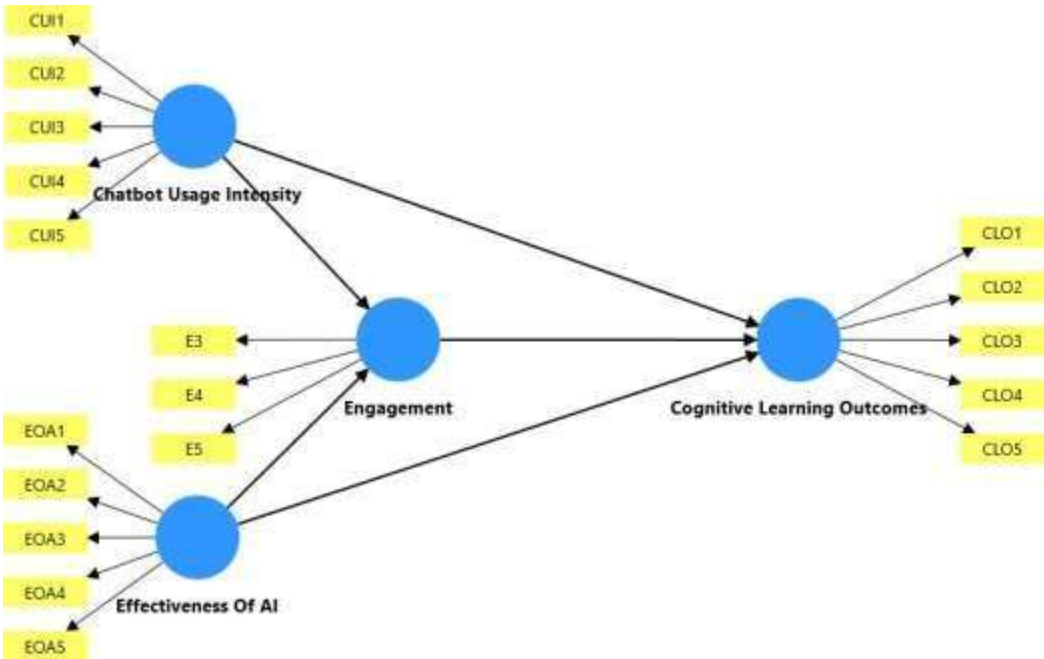

Figure 2. The model proposed in this study

Hypothesis:

H1: Chatbot Usage Intensity has a positive and significant effect on students' Cognitive Learning Outcomes.
H2: Effectiveness of AI has a positive and significant effect on students' Cognitive Learning Outcomes.
H3: Chatbot Usage Intensity has a positive and significant effect on Engagement.
H4: Effectiveness of AI has a positive and significant effect on Engagement.
H5: Engagement has a positive and significant effect on Cognitive Learning Outcomes.
H6: Student engagement mediates the effect of Chatbot Usage Intensity on Cognitive Learning Outcomes.
H7: Student engagement mediates the effect of Effectiveness of AI on Cognitive Learning Outcomes.

RESULTS AND DISCUSSION

As an initial stage of presenting the research results, the demographic characteristics of the respondents are described to provide an overview of the group of students involved in this study. A total of 88 active students from Makassar State University who use artificial intelligence-based chatbots in their learning activities participated in this study. Table 2 includes information on gender, age, semester, class year, major, digital device ownership, frequency of AI use, and the purpose of AI technology utilization. This profile provides context regarding the level of technological readiness and patterns of AI use, which form the basis for understanding the variations in chatbot usage intensity in the subsequent analysis.

Table 2. Respondent Demographic Data

Category	Description	Percentage
Gender	Male	35.2%
	Female	64.8%
Age	17	3.4%
	18	31.8%
	19	45.5%
	20	14.8%
	21	4.5%
Semester	I	35.2%
	III	61.4%
	V	1.1%
	VII	2.3%
Generation	2022	2.3%
	2023	1.1%
	2024	61.4%
	2025	35.2%
Department (Major)	Non STEM	28.4%
	STEM	71.6%
Ownership of Digital Devices	No	2.3%
	Yes	97.7%
Frequency of AI Usage	1–2 times a week	6.8%
	3–5 times a week	30.7%
	Rarely	4.5%
	Every day	58.0%
The Main Purpose of AI Use	Study Course Material	12.5%
	Assist with Assignment Writing	5.7%
	Search for References	18.2%
	Combination (Study, Assignment, Reference)	48.9%

Source: Processed data, 2025

Overall, female respondents dominated (64.8%), a pattern often found in digital education research due to their tendency to participate more in academics. The majority were aged 18–20, especially 19 years old, indicating that most were first-year students who were adapting to technology-based learning. The semester distribution also showed a predominance of third-semester students (61.4%), followed by first-semester students (35.2%), indicating that the respondents already had basic experience in using learning technology but were still at an academic stage that required digital tool support.

Based on cohort, students enrolled in 2024 constitute the largest group (61.4%), indicating that new students have been exposed to a learning ecosystem integrated with AI technology since the beginning of their studies. The majority of respondents come from STEM fields (71.6%), which reflects a relatively higher level of technological readiness compared to other fields. The majority of participants own personal digital devices (97.7%), while a small portion do not (2.3%), indicating that technological access barriers in this study are relatively low. The high intensity of AI use is evident from the fact that 58.0% of students use AI every day and 30.7% use it 3-5 times a week, while 6.8% use it 1-2 times a week and 4.5% rarely use it. The most dominant purpose of use is the

combination category (learning lecture material, helping with writing assignments, and searching for references) at 48.9%, indicating that AI is used multifunctionally in academic activities.
Table 3 presents the results of the instrument quality evaluation, which includes four research constructs, namely Chatbot Usage Intensity (CUI), Effectiveness of AI (EOA), Engagement (E), and Cognitive Learning Outcomes (CLO). The evaluation was conducted based on outer loading, Composite Reliability (CR), Rho_A, and Average Variance Extracted (AVE), all of which were used to ensure the fulfillment of convergent validity and construct reliability in accordance with PLS-SEM standards. (Hair et al., 2017; Hair Jr. et al., 2021).

Tabel 3. Results of Convergent Validity and Construct Reliability Evaluation

Construct and Items	Outer Loading	Rho_A	Composite Realibility (CR)	Average Variance Extracted (AVE)
Chatbot Usage Intensity (CUI)				
CUI1	0.788			
CUI2	0.857			
CUI3	0.803	0.901	0.922	0.703
CUI4	0.869			
CUI5	0.801			
Effectiveness Of AI (EOA)				
EOA1	0.860			
EOA2	0.813			
EOA3	0.831	0.908	0.931	0.729
EOA4	0.751			
EOA5	0.928			
Engagement (E)				
E3	0.881			
E4	0.870	0.889	0.914	0.679
E5	0.904			
Cognitive Learning Outcomes (CLO)				
CLO1	0.881			
CLO2	0.829			
CLO3	0.895	0.867	0.916	0.783
CLO4	0.852			
CLO5	0.808			

Source: Processed data, 2025

In general, the test results show that all constructs have met the measurement quality criteria. In the CUI construct, the indicators show a consistent contribution in explaining AI chatbot usage behavior, as reflected in the high internal reliability and AVE values. These findings indicate that the instrument is capable of capturing the intensity of AI usage in a stable and representative manner in accordance with the research concept. A similar pattern is seen in the EOA construct, where the indicators show good measurement strength in describing students' perceptions of the effectiveness of chatbots in assisting academic understanding. CR and AVE values within the ideal range indicate that this construct is consistently structured and capable of explaining most of the indicator variance.
The Engagement (E) construct also showed adequate measurement performance. However, at the outer model evaluation stage, two Engagement indicators (E1 and E2) were eliminated because their outer loading values were below the feasibility limit (< 0.70), meaning they did not optimally represent the construct. The removal of these indicators was done to improve convergent validity and ensure that the remaining indicators truly reflect the concept of Engagement in this study. The retained indicators show a strong correlation with the construct, indicating that the aspect of active student participation in using AI is well reflected in the model. The high reliability value reinforces that the Engagement construct can be used validly to test the relationship with other variables in the inner model. Meanwhile, the CLO construct shows the highest AVE value among all constructs, indicating that this research instrument is very effective in measuring students' cognitive abilities. This confirms that the CLO indicator is not only internally consistent but also has strong explanatory power for latent variables.
Table 4 presents the results of discriminant validity evaluation using the Fornell-Larcker approach, which is the main procedure in PLS-SEM to ensure that each construct in the model has clear

conceptual differences and does not overlap. Discriminant validity is a fundamental aspect of measurement models because it shows whether latent variables are truly independent of one another in both theoretical and empirical representations (Hair et al., 2017; Hair Jr. et al., 2021). The core principle of this criterion is that the square root of the AVE of a construct must be greater than its correlation with all other constructs. If this requirement is met, then the construct can be said to have adequate discriminant validity.

Table 4. Results of the Fornell-Lacker Validity Test

	Effectiveness of AI	Cognitive Learning Outcomes	Chatbot Usage Intensity	Engagement
Effectiveness of AI	0.839			
Cognitive Learning Outcomes	0.825	0.854		
Chatbot Usage Intensity	0.628	0.777	0.824	
Engagement	0.815	0.834	0.663	0.885

Source: Processed data, 2025

The test results in Table 4 show that all constructs in this study have met the discriminant validity criteria according to Fornell-Larcker. The square root of AVE for each construct is consistently higher than the correlation value between latent variables, indicating that the indicators in one construct have a stronger connection to their own construct than to other constructs. In other words, each variable in the model has a clear conceptual identity and does not overlap in meaning, which is an important prerequisite for ensuring the integrity of the structural model. The Effectiveness of AI (EOA) construct shows strong discriminative ability, where the AVE square root value is greater than all its correlations with the CUI, Engagement (E), and Cognitive Learning Outcomes (CLO) constructs. These findings indicate that students' perceptions of AI effectiveness are measured consistently without being mixed with the dimensions of chatbot use, engagement, or learning outcomes. A similar pattern is also seen in the CLO construct, which shows high conceptual separation strength, so that cognitive learning outcomes are measured independently and are not influenced by other constructs in the model.

Similarly, the Chatbot Usage Intensity (CUI) and Engagement (E) constructs show an adequate discriminant structure. The AVE square root of both constructs is higher than their correlation with other constructs, confirming that chatbot usage patterns and student engagement are theoretically distinct dimensions even though they are interrelated in the context of the structural model. With all these criteria met, the research model can be said to have strong discriminant validity, making it feasible to proceed to the inner model analysis stage. The fulfillment of discriminant validity ensures that the causal relationships tested in the next stage truly represent the interactions between different latent variables and are not conceptually mixed.

Table 5. Results of Testing the Relationship between Latent Constructs

	Hypothesis	Path Coefficient	T-Statistics	P-Values	Decision
H1	Chatbot Usage Intensity -> cognitive learning outcomes	0.345	3.710	0.000	Positive and significant
H2	Effectiveness of AI -> cognitive learning outcomes	0.342	2.469	0.007	Positive and significant
H3	Chatbot Usage Intensity -> Engagement	0.250	2.291	0.011	Positive and significant
H4	Effectiveness of AI -> Engagement	0.658	7.187	0.000	Positive and significant
H5	Engagement -> cognitive learning outcomes	0.327	2.749	0.003	Positive and significant
H6	Chatbot Usage Intensity -> Engagement -> cognitive learning outcomes	0.082	1.618	0.053	Positive and insignificant
H7	Effectiveness of AI -> Engagement -> cognitive learning outcomes	0.215	2.724	0.003	Positive and significant

Sumber: Data diolah, 2025

The test results show that most of the relationships between constructs in the model are positive and significant. Both Chatbot Usage Intensity (CUI) and Effectiveness of AI (EOA) have a significant direct influence on CLO, indicating that chatbot usage intensity and perception of AI quality both contribute to improving students' cognitive abilities. These findings confirm that the use of chatbots not only serves as a technical tool but also supports the process of knowledge internalization when used consistently and effectively. In addition, the Engagement (E) variable was also found to have a significant direct effect on CLO, indicating that students' active engagement in interactions with AI technology plays an important role in strengthening their learning process. In the exogenous path to Engagement, the findings show that EOA is the strongest predictor, followed by CUI. This indicates that the perception of AI effectiveness is the main factor that encourages students to be more actively involved when using chatbots, while usage intensity still contributes, albeit with a more moderate influence.

In testing the mediation effect, only the relationship between Effectiveness of AI and CLO through Engagement proved to be significant. Meanwhile, mediation in the relationship between Chatbot Usage Intensity and CLO through Engagement showed a positive direction of influence, but was not statistically significant, so the mediating role of Engagement in this path could not be confirmed. These results indicate that student engagement is a mechanism that bridges the influence of AI effectiveness on learning outcomes, but it has not been conclusively proven to bridge the influence of chatbot usage intensity on cognitive abilities. Thus, AI Effectiveness plays a dominant role, both directly and indirectly, in explaining variations in students' cognitive learning outcomes.

Table 6 shows the amount of variance in the endogenous construct that can be explained by the exogenous variables in the research model. The R^2 value is the main indicator for assessing the predictive ability of structural models and is widely used in PLS-SEM to assess how well exogenous constructs explain endogenous constructs (Hair et al., 2017; Hair Jr. et al., 2021). In this study, the two endogenous constructs analyzed were Cognitive Learning Outcomes (CLO) and Engagement (E).

Table 6. R Square (R^2) of Endogenous Variable

Endogenous Variable	R Square (R^2)
Cognitive Learning Outcomes	0.823
Engagement	0.702

Source: Processed data, 2025

The results show that R^2 for CLO is 0.823, which means that 82.3% of the variation in students' cognitive learning abilities can be explained by the variables Chatbot Usage Intensity, Effectiveness of AI, and Engagement. This value falls into the substantial category, meaning that the model has a very strong explanatory power for cognitive learning outcomes. Thus, most of the changes in CLO can be understood through a combination of chatbot usage intensity, perceptions of AI effectiveness, and the level of student engagement in AI-based learning processes. However, the high R^2 value also needs to be interpreted with caution, given that all data were obtained through a self-report instrument at a single measurement point, so there is a possibility of common method bias that could increase the correlation between constructs. Therefore, further studies using multi-source or longitudinal designs are recommended to re-examine the explanatory power of this model in a broader population.

Meanwhile, the Engagement construct has an R^2 value of 0.702, indicating that 70.2% of the variation in student engagement is explained by Chatbot Usage Intensity and Effectiveness of AI. This value falls into the moderate to substantial category, indicating that these two exogenous variables have strong predictive power in shaping the level of student engagement when using artificial intelligence-based chatbots. This interpretation still shows the predictive power of the model, but it should be understood as a contextual finding that is still potentially influenced by sample characteristics and uniform measurement methods.

The results of the study show that most of the relationships in the model are significant and consistent with previous findings. The positive influence between Chatbot Usage Intensity (CUI) and Cognitive Learning Outcomes (CLO) confirms that the more often students use chatbots, the greater their chances of understanding the material through repeated interactions and quick corrections to misconceptions (Azzura & Sartono, 2025; Firjatullah et al., 2025). Similarly, Effectiveness of AI (EOA) has been shown to improve CLO, indicating that the quality, clarity, and accuracy of AI responses play an important role in strengthening student understanding(Araujo et al., 2023; Mayasari et al., 2023).

These findings confirm that AI effectiveness is a key factor in the success of digital learning because it not only supports access to information but also ensures that the information is relevant and easily internalized by students.

The relationship between CUI and Engagement was also found to be positive and significant. Students who used the chatbot more frequently tended to be more engaged in learning, consistent with previous research emphasizing that repeated digital interactions can increase participation and concentration in learning (Sahabuddin et al., 2025; Zhang et al., 2023). In addition, EOA emerged as the strongest predictor of Engagement. This indicates that the quality of AI responses not only affects understanding but also encourages active student engagement, because when chatbots are considered accurate and clear, students are more motivated to explore the material further and engage in a dialogic learning process (OECD, 2020). Engagement itself has been shown to have a significant effect on CLO, supporting the view that active engagement promotes deeper understanding (Firjatullah et al., 2025).

In the mediation pathway, it was found that the indirect effect of CUI on CLO through Engagement was positive but not statistically significant, so the role of Engagement as a mediator in this relationship could not be confirmed. This means that the intensity of chatbot use still has a direct effect on cognitive ability, while the mechanism of engagement has not been conclusively proven as a bridge for this effect. This finding is consistent with studies stating that frequency of use is not always synonymous with meaningful engagement if the quality of interaction or AI feedback is not optimal (Mayasari et al., 2023). Conversely, Engagement has been proven to mediate the relationship between EOA and CLO, indicating that the quality of AI responses not only has a direct effect but also increases student engagement, which ultimately strengthens their learning outcomes (OECD, 2020; Zhang et al., 2023) Thus, the effectiveness of AI plays a dominant role both as a direct influence and through increased Engagement.

The additional R^2 results provide a stronger explanation of the model's ability to predict dependent variables. An R^2 value of 0.823 for CLO indicates that the model is able to explain most of the variation in student learning outcomes through a combination of CUI, EOA, and Engagement. Meanwhile, an R^2 value of 0.702 for Engagement indicates that this variable is strongly explained by CUI and EOA. Although these values indicate high model predictive power according to PLS-SEM evaluation standards (Hair et al., 2017; Sarstedt et al., 2021) their interpretation needs to be done carefully because all variables are measured through self-report instruments at one point in time. This condition has the potential to cause common method bias, which can increase the correlation between constructs and increase the R^2 value. Therefore, retesting with a multi-source, longitudinal, or experimental design is needed to ensure the stability of the model's explanatory power in a broader context.

These findings have important implications for the development of AI-based learning in higher education. The quality of AI responses needs to be a top priority, as it has been shown to significantly affect engagement and learning outcomes. The intensity of use also needs to be encouraged, but chatbot integration should emphasize the quality of interaction, not just frequency. Institutions can direct the use of chatbots through dialogue-based tasks, reflective exercises, or problem-based learning scenarios so that AI interactions truly enrich students' cognitive processes.

Although this study has strong theoretical and empirical contributions, there are several limitations. The use of self-report data has the potential to cause perception bias, and respondents from only one institution limit the generalization of the findings, so the results of this study are still contextual. Future research could involve more institutions and add other variables such as learning motivation, digital literacy, or perceived usefulness. A longitudinal or experimental approach is also recommended to provide a deeper understanding of the effectiveness of chatbots in various learning contexts, while testing the consistency of findings in a more diverse population

CONCLUSION

This study demonstrates that both AI chatbot usage intensity and perceived AI effectiveness contribute positively to students' cognitive learning outcomes, with student engagement playing a central explanatory role. While frequent chatbot use enhances learning outcomes directly, the mediating role of engagement is only significant for AI effectiveness, indicating that the quality and

pedagogical usefulness of AI interactions are more influential than usage frequency alone. These findings confirm that effective AI-supported learning is shaped not merely by exposure to technology, but by how meaningfully students engage with AI-generated feedback and guidance.
From a life-course education perspective, these results highlight higher education as a formative stage in early adulthood where interaction patterns with AI may influence students' long-term learning dispositions. Engagement-driven AI use supports cognitive development and learning sustainability, which are essential foundations for lifelong learning. Conversely, reliance on frequent but low-quality AI interactions may limit deeper cognitive engagement.
Theoretically, this study extends research on artificial intelligence in education by positioning student engagement as a key mechanism linking AI chatbot use and cognitive learning outcomes within a life-course framework. Practically, the findings suggest that higher education institutions should emphasize the pedagogical effectiveness of AI chatbots through structured learning tasks, reflective feedback, and active learning integration, rather than encouraging usage intensity alone. Despite its contributions, this study is limited by its cross-sectional design, self-reported measures, and single-context sample. Future research should employ longitudinal or experimental approaches, incorporate indicators of AI interaction quality, and examine diverse educational stages to further advance understanding of AI-supported lifelong and life-course education.

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AUTHOR CONTRIBUTION STATEMENT

MNS conceptualized the study, developed the research framework, and drafted the original manuscript. MNAH contributed to instrument development, data collection, and preliminary data analysis. DF conducted data processing, statistical analysis using PLS-SEM, and interpretation of empirical results. SA provided theoretical supervision, methodological validation, and critical revisions of the manuscript.

AI DISCLOSURE STATEMENT

The authors used ChatGPT solely as a language-support tool for grammatical refinement, clarity improvement, and structural editing during manuscript preparation. All substantive scholarly activities including research design, theoretical development, data collection, statistical analysis, interpretation of results, and formulation of conclusions were conducted entirely by the authors. The authors critically reviewed and edited all AI-assisted content and take full responsibility for the originality, accuracy, and integrity of the published work.

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