Journal of Innovative and Creativity
Journal Homepage: https://joecy.org/index.php/joecy
e-mail: galungwaknook@gmail.co

Faculty of Education
University of Pahlawan Tuanku Tambusai
ISSN 2775-771X (Online)
ISSN 2962-570X (Printed)
5 (2) 2025, Page: 25035-25042

AI Chatbots as Academic Assistants: Do Frequency and Perceived Usefulness Drive Learning Motivation?

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Published: May , 2025

ABSTRACT

The study purpose was to examine whether the frequency of using AI chatbots and students' perceived usefulness of those chatbots are associated with learning motivation among economics undergraduates at Cenderawasih University.
Materials and methods. A quantitative explanatory, cross-sectional survey was administered to 89 economics students selected proportionally across semesters. Learning motivation was measured via indicators of interest in study, enthusiasm for assignments, satisfaction with learning, and consistency in study habits. After pilot testing and instrument refinement, data were analyzed using simple linear regression (overall utilization) and multiple regression (frequency and perceived usefulness), following normality, multicollinearity, and heteroscedasticity checks.
Results show a statistically significant model ($F = 54.442$, $p < .001$) explaining a substantial share of variance in learning motivation ($R^2 = 0.559$; Adjusted $R^2 = 0.548$). Perceived usefulness exerted a larger effect ($\beta = 0.550$) than frequency ($\beta = 0.343$), with both predictors highly significant ($p < .001$). The joint model of frequency and perceived usefulness predicted motivation robustly ($p < .001$), supporting all three hypotheses.

Keywords: AI chatbots; Cenderawasih University; economics students; frequency of use; learning motivation; Papua; perceived usefulness; regression analysis.

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INTRODUCTION

The rapid advancement of artificial intelligence (AI) has brought significant transformation to the field of education. Among the various AI applications, chatbots have emerged as innovative tools designed to assist students in their academic activities. AI chatbots can provide instant feedback, clarify complex concepts, suggest relevant resources, and act as virtual tutors accessible at any time. For university students, especially those studying economics where analytical skills and continuous engagement are essential, the integration of AI chatbots has the potential to reshape learning experiences.

Learning motivation plays a crucial role in determining students' academic performance. Motivated students tend to be more engaged in their studies, persistent in solving problems, and proactive in exploring knowledge beyond classroom instruction. However, many students face challenges such as limited access to lecturers outside class hours, difficulty in finding reliable references, and declining enthusiasm due to workload pressures. In this context, AI chatbots can serve as academic assistants that bridge these gaps by providing flexible, personalized, and immediate support.

Recent studies show mixed results regarding the effectiveness of AI chatbots in higher education (Eteng-Uket, 2025; Mourabit et al., 2025; Segovia-García, 2024). On the positive side, chatbots can enhance student engagement, motivation, and academic outcomes by offering interactive and user-friendly assistance (Mourabit et al., 2025, Pappagallo, 2024; Eteng-Uket, 2025) However, concerns include overdependence on technology, reduced critical thinking, and the possibility of inaccurate responses. These variations suggest the need for context-specific studies to understand how AI

chatbots impact students in different academic environments (Nguyen e al., 2024, Segovia-García 2024, Brändle et al., 2025).
At Cenderawasih University, economics students are increasingly exposed to digital learning tools, yet the role of AI chatbots as academic assistants remains underexplored. Considering the growing integration of AI in education and the importance of learning motivation for academic success, it becomes essential to examine the influence of chatbot usage on students' motivation. This research seeks to analyze whether AI chatbots significantly affect the learning motivation of economics students at Cenderawasih University, thereby contributing to the broader discourse on digital innovation in higher education.

Artificial Intelligence (AI) refers to the capability of computer systems to perform tasks that typically require human intelligence—such as reasoning, learning, and problem solving (Russell & Norvig, 2021). In higher education, AI is increasingly embedded in teaching–learning workflows through adaptive systems, virtual tutors, automated feedback, and intelligent grading, enabling personalized support and streamlining routine tasks (Chen et al., 2020). Empirical and review evidence indicates that such tools can improve accessibility, efficiency, and flexibility in digital or hybrid learning environments (Holmes et al., 2022).

AI chatbots—conversational agents powered by natural language processing—serve as on-demand academic assistants that answer questions, curate resources, scaffold assignments, and deliver immediate feedback (Følstad & Brandtzaeg, 2020). Their 24/7 availability helps overcome time and place constraints in seeking help (Essel et al., 2022), and studies report gains in engagement, satisfaction, and task efficiency following adoption in university courses (Labadze, 2023). At the same time, the literature cautions about accuracy limits, overreliance, and ethical concerns in learning contexts that require deliberate instructional design (Følstad & Brandtzaeg, 2020; Essel et al., 2022).

Learning motivation—an internal drive that initiates, sustains, and directs learning—predicts engagement, persistence, and academic achievement (Ryan & Deci, 2020; Schunk et al., 2019). Motivation is commonly differentiated into intrinsic (interest/enjoyment) and extrinsic (external rewards) components and is shaped by pedagogical approaches, resource availability, social support, and digital tools that reduce friction and enhance perceived value (Ryan & Deci, 2020; Schunk et al., 2019).

Frequency of Chatbot Use and Learning Motivation

Frequent interaction with a responsive academic assistant can reinforce productive study routines, lower barriers to help-seeking, and sustain momentum in coursework—mechanisms associated with stronger motivation (Ryan & Deci, 2020; Schunk et al., 2019). Because chatbots provide immediate assistance and are continuously available (Essel et al., 2022), recurrent use is likely to translate into more consistent engagement and timely problem resolution, which the broader AI-in-education literature links to improved learning experiences (Chen et al., 2020; Holmes et al., 2022). Accordingly, H_1 posits a positive, significant association between the frequency of chatbot use and learning motivation.

Perceived Usefulness and Learning Motivation

Perceived usefulness captures beliefs that chatbot support meaningfully improves learning effectiveness (e.g., clarifying difficult concepts, streamlining tasks, and offering relevant resources). When academic tools are judged instrumentally valuable, motivation typically rises because effort is seen as more efficacious and worthwhile (Ryan & Deci, 2020; Schunk et al., 2019). Prior work documents motivational gains where AI support is accurate, responsive, and aligned with course demands (Følstad & Brandtzaeg, 2020; Chiu et al., 2023; Hanshaw et al., 2024; Labadze, 2023),

while also noting the need to avoid dependency that may dampen self-regulated learning (Eteng-Uket et al., 2025). Hence, H_2 anticipates a positive, significant effect of perceived usefulness on learning motivation.

Joint Contributions of Frequency and Perceived Usefulness to Learning Motivation

The literature suggests that frequent access and strong perceived usefulness operate together: availability and repeated use amplify exposure to helpful feedback, while perceived value encourages sustained engagement with the tool (Chen et al., 2020; Holmes et al., 2022; Essel et al., 2022). In combination, these factors are expected to explain meaningful variance in motivational outcomes, provided that use remains purposeful and academically grounded (Følstad & Brandtzaeg, 2020; Eteng-Uket et al., 2025). Given limited evidence from Indonesian higher education—particularly in eastern regions such as Papua. Thus, H_3 posits that frequency of use and perceived usefulness, considered together, have a positive and significant effect on learning motivation among economics students at Cenderawasih University.

METHOD

This research adopts a quantitative explanatory design to analyze the influence of AI chatbots as academic assistants on the learning motivation of economics students at Cenderawasih University. The study population consists of 779 students, and using the Slovin formula with a 10% margin of error, a minimum sample of 89 respondents is required. Stratified random sampling is applied to ensure proportional representation of students across different semesters. Data are collected using structured questionnaires supported by limited interviews to provide contextual insights.

The research instrument was first tested with 3 students to assess validity and reliability. From this initial pilot, three items were found to be invalid and subsequently removed, leaving a final questionnaire with 30 items. These consist of 10 items measuring the frequency of chatbot use, 10 items assessing perceived usefulness, and 10 items evaluating overall utilization. Learning motivation is measured through indicators related to interest in study, enthusiasm for completing assignments, satisfaction with learning, and consistency in study habits. Validity is tested using item–total correlation, while reliability is examined with Cronbach's Alpha, where a threshold of $\alpha \geq 0.70$ is considered acceptable.

Data analysis begins with descriptive statistics to summarize respondent characteristics and variable tendencies. Before conducting regression analysis, classical assumption tests are carried out to confirm that the data meet the necessary requirements. These tests include the normality test to ensure residuals are normally distributed, the multicollinearity test to detect whether independent variables are excessively correlated, and the heteroscedasticity test to confirm the constancy of residual variance. Once these assumptions are satisfied, regression analysis is performed. Simple linear regression is used to assess the overall effect of chatbot utilization on learning motivation, while multiple regression is applied to test the influence of frequency, perceived usefulness, and overall utilization separately. Hypothesis testing is conducted using the t-test at a significance level of $\alpha = 0.05$, and the coefficient of determination (R^2) is calculated to measure the extent to which chatbot utilization explains variations in learning motivation. The results are then interpreted in light of relevant theories and previous research.

FINDING AND DISCUSSION

The data were collected from 89 economics students at Cenderawasih University, representing the sample determined by the Slovin formula with a 10% margin of error. Respondents were proportionally selected across semesters to ensure diversity in academic experience. Descriptive analysis showed that 74% of the students used AI chatbots frequently for academic activities, while 66% considered the chatbots useful in supporting their learning tasks. Overall, 68% expressed positive perceptions of chatbot use. Students generally reported moderate to high levels of learning

motivation, with those who used chatbots more often showing greater enthusiasm for assignments and steadier study habits than peers who used them rarely.

Instrument testing began with 35 pilot questionnaires to 30 respondents. Of these, 5 items were found invalid and removed, leaving 30 valid items. Validity testing confirmed that all retained items had correlation coefficients above the r-table value (0.207 for N=89), while reliability testing showed Cronbach's Alpha values exceeding 0.70 for each construct, indicating high internal consistency. These results confirmed that the questionnaire was both valid and reliable for measuring chatbot utilization and learning motivation.

Before conducting regression analysis, classical assumption tests were performed. The normality test, using the Kolmogorov–Smirnov method, produced a significance value greater than 0.05, indicating normally distributed residuals as seen bellow:
Multicollinearity testing showed Variance Inflation Factor (VIF) values below 10 and tolerance

One-Sample Kolmogorov-Smirnov Test

			Unstandardized Residual
N			89
Normal P			.0000000
			7.23830192
Most Extre			.040
			.039
	Negative		-.040
Test Statistic			.040
Asymp. Sig. (2-tailed)[c]			.200[d]
Monte Carlo Sig. (2-tailed)[e]	Sig.		.983
	99% Confidence Interval	Lower Bound	.979
		Upper Bound	.986

a. Test distribution is Normal.

b. Calculated from data.

c. Lilliefors Significance Correction.

d. This is a lower bound of the true significance.

e. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2000000.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	Frequency	.864	1.157
	Preceived Usefulness	.864	1.157

a. Dependent Variable: Utilization

Table 2. Result of Multicollinearity testing

values above 0.10, suggesting no multicollinearity among independent variables as seen in the table bellow:

The heteroscedasticity test using Glejser's method revealed no significant relationship between residuals and independent variables, confirming the absence of heteroscedasticity. These results indicated that the data met the assumptions required for regression analysis as seen in the table bellow:

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	6.639	1.517		4.376	<.001
	Frequency	.036	.045	.092	.803	.424
	Preceived Usefulness	-.061	.041	-.172	-1.503	.137

a. Dependent Variable: Abs_RES

Table 3. Model Summary — multiple regression predicting Utilization from Perceived Usefulness and Frequency (N = 89)

Assumption diagnostics indicated approximately normal residuals, constant variance, and acceptable multicollinearity. With these prerequisites satisfied, the analysis proceeded to multiple regression to estimate the unique contributions of Frequency and Perceived Usefulness (PU) to Utilization (see Tables 4–6):

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.747[a]	.559	.548	7.322

a. Predictors: (Constant), Preceived Usefulness, Frequency

Table 4. Model Summary — multiple regression predicting Utilization from Perceived Usefulness and Frequency (N = 89)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5837.415	2	2918.707	54.442	<.001[b]
	Residual	4610.585	86	53.611		
	Total	10448.000	88			

a. Dependent Variable: Frequency and Perceived Usefulness

b. Predictors: (Constant), Preceived Usefulness, Frequency

Table 5. ANOVA — overall significance of the Utilization regression model

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.964	2.680		1.479	.143
	Frequency	.356	.080	.343	4.449	<.001
	Preceived Usefulness	.512	.072	.550	7.133	<.001

a. Dependent Variable: Frequency and Perceived Usefulness

Table 6. Coefficients — effects of Perceived Usefulness and Frequency on Utilization.

The Model Summary table shows us how well the model predicts the dependent variable, which in this case is not specified in this table alone. We see that the R-squared value is 0.559, which means that the predictor variables—Frequency and Perceived Usefulness—account for 55.9% of the

variance in the dependent variable. The Adjusted R-squared of 0.548 is a more conservative estimate of the model's predictive power. The R-value of 0.747 indicates a strong positive correlation between the predictors and the dependent variable. The ANOVA table further assesses the overall significance of the model. The F-value of 54.442 with a significance level (Sig.) of <.001 indicates that the model as a whole is statistically significant and a good fit for the data.

The Coefficients table provides details on the contribution of each individual predictor variable. The Unstandardized Coefficients (B) show the change in the dependent variable for a one-unit increase in the predictor. For Frequency, the B value is 0.356, and for Perceived Usefulness, it is 0.512. The Standardized Coefficients (Beta) allow for a direct comparison of the predictors' impact, showing that Perceived Usefulness has a stronger influence (Beta = 0.550) than Frequency (Beta = 0.343). Both predictors are highly significant, as indicated by their Sig. values of <.001, which are well below the conventional threshold of 0.05. This confirms that both Frequency and Perceived Usefulness are important predictors in this model. Based on the a. Dependent Variable footnotes, the model appears to be predicting a third, unspecified variable using "Frequency" and "Perceived Usefulness" as predictors.

DISCUSSION

H1 (Frequency → Learning Motivation).

First hypothesis — accepted. The analysis supports the claim that more frequent use of the chatbot is linked with higher learning motivation, and this effect is statistically reliable. This acceptance aligns with motivation theory and prior work showing that frequent, on-demand support lowers friction, stabilizes study routines, and keeps students engaged, as discussed by Ryan and Deci, Schunk and colleagues, and studies of always-available academic assistance by Essel and co-authors, Chen and co-authors, and Holmes and co-authors. It is also consistent with reports of improved engagement from purposeful chatbot use noted by Mourabit and colleagues, Eteng-Uket, and Pappagallo.

H2 (Perceived Usefulness → Learning Motivation).

Second hypothesis — accepted. Perceived usefulness demonstrates a clear and stronger positive association with learning motivation, so this hypothesis is accepted. The result echoes motivation research indicating that students invest more effort when a tool is experienced as genuinely helpful for learning, as outlined by Ryan and Deci and by Schunk and colleagues. It also concurs with findings that well-designed chatbots—accurate, responsive, and aligned with course tasks—enhance satisfaction, efficiency, and motivational outcomes, consistent with Følstad and Brandtzaeg, Labadze, Chiu and colleagues, Hanshaw and colleagues, and Eteng-Uket.

H3 (Frequency + Perceived Usefulness jointly → Learning Motivation).

Third hypothesis — accepted. When considered together, frequency of use and perceived usefulness produce a robust, statistically significant model of learning motivation; therefore, the joint-effects hypothesis is accepted. This pattern mirrors the broader AI-in-education literature, where dependable access amplifies exposure to helpful feedback and perceived value sustains continued use, as noted by Chen and co-authors, Holmes and co-authors, and Essel and co-authors. Amid mixed reports about chatbots in higher education, the present findings fall on the positive side documented by Mourabit and colleagues, Segovia-García, Eteng-Uket, Pappagallo, Nguyen and colleagues, and Brändle and colleagues.

CONCLUSIONS

This study set out to examine whether the frequency of using AI chatbots and students' perceptions of their usefulness relate to learning motivation among economics students at Cenderawasih University. The analysis shows that both factors are positively associated with motivation, with perceived usefulness emerging as the stronger driver, and their joint contribution forming a robust model. Taken together, these results support all three hypotheses and add context-specific evidence from Papua that AI chatbots, when integrated purposefully as academic assistants, can play a constructive role in students' day-to-day learning.

For practice, the findings suggest several actionable steps. Lecturers can embed chatbots into course workflows for clarifying concepts, guiding assignments, and curating resources, while providing brief orientation on effective and ethical use. Tasks should encourage guided problem-solving rather than simple copy-paste answers, and feedback loops can nudge students toward reflection and independent thinking. Program leaders may consider aligning chatbot use with learning outcomes, offering usage guidelines, and monitoring quality and accuracy so that the tools complement—not replace—core academic skills.

This work has limitations that point to future research. The design is cross-sectional and relies on self-reports from a single program, which may limit generalizability and causal claims. Subsequent studies could use longitudinal or experimental approaches, incorporate usage logs, and explore mediating and moderating factors such as self-efficacy, digital literacy, or help-seeking behaviors. Replication across faculties and institutions, combined with qualitative insights, would help refine how chatbot access and perceived value can be balanced to sustain motivation while preserving critical and independent learning..

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