Volume: 28, Number: 2, September 2026, pp. 156-164
p-ISSN: 1410-8771, e-ISSN: 2580-4812
https://doi.org/10.37303/likhitaprajna.v28i2.982

LIKHITAPRAJNA Jurnal Ilmiah
Fakultas Keguruan dan Ilmu Pendidikan

MULTI-PLATFORM AI USE AND STUDENT LEARNING MOTIVATION IN EDUCATIONAL TECHNOLOGY PROGRAM

Azzahra Nurrahmi[1], Mastur[2], Sulistyo Rini[3]
[1]Universitas Lambung Mangkurat, Banjarmasin, Indonesia, 2110130320017@mhs.ulm.ac.id
[2]Universitas Lambung Mangkurat, Banjarmasin, Indonesia, mastur@ulm.ac.id
[3]Universitas Lambung Mangkurat, Banjarmasin, Indonesia, sulistyo.rini@ulm.ac.id

ARTICLE INFO

Article history:
Received 18 June 2026
Revised 6 July 2026
Accepted 6 August 2026

Keywords:
Artificial Intelligence
Learning Media
Learning Motivation
Educational Technology
Higher Education

To cite this article:
Nurrahmi, A., Mastur, M., & Rini, S. (2026). Multi-Platform AI Use and Student Learning Motivation in Educational Technology Program. *Jurnal Likhitaprajna*, *28*(2), 156-164. https://doi.org/10.37303/likhitaprajna.v28i2.982

ABSTRACT

The rapid advancement of Artificial Intelligence (AI) platforms has opened transformative opportunities for improving the quality of learning in higher education, yet empirical studies comprehensively examining multi-platform AI use and student learning motivation in the Indonesian context remain limited. This study analyzes the relationship between the use of AI-based learning media—encompassing ChatGPT, Perplexity AI, Canva AI, and Gamma AI—and the learning motivation of students in the Educational Technology Study Program, FKIP, Universitas Lambung Mangkurat, using a quantitative correlational design with 40 students (60% female, 40% male) selected through purposive sampling. Data were collected using a validated 37-item Likert-scale questionnaire (Cronbach's $\alpha = 0.966$) and analyzed using Spearman Rank Correlation ($\alpha = 0.05$). The results show that the majority of tested variable pairs exhibited a significant positive correlation, with AI use for end-of-semester assignments showing the strongest correlation with learning motivation ($r_s = 0.837$, $p < 0.001$). These findings underscore that systematic and competency-based AI use is a strong predictor of learning motivation, highlighting the need for structured AI literacy programs in higher education institutions.

Corresponding Author:
Mastur
Universitas Lambung Mangkurat, Banjarmasin, Indonesia, mastur@ulm.ac.id

INTRODUCTION

The dynamics of higher education in the post-pandemic era are characterized by an unprecedented acceleration in the adoption of digital technology. Among various technological innovations, generative Artificial Intelligence (AI)—particularly large language models such as Chat GPT has shown the fastest technology adoption trajectory in consumer history, surpassing 100 million active users within two months of its November 2022 launch (Baidoo-Anu & Owusu Ansah, 2023). This phenomenon has compelled universities worldwide to reassess how students learn, create, and construct academic knowledge.

In Indonesia, internet penetration reaching 67.29% of the population—approximately 185.3 million users (BPS, 2023)—combined with a large proportion of young adults, has created an ecosystem highly conducive to AI adoption in education. Indonesia ranks among the top ten countries in AI adoption growth during 2022–2024 (Kemp, 2024), and Indonesian students increasingly integrate multiple AI platforms into academic routines: ChatGPT for conceptual explanation, Perplexity AI for verified reference retrieval, Canva AI for visual content production, and Gamma AI for presentation development.

The Educational Technology Study Program at FKIP, Universitas Lambung Mangkurat (ULM), occupies a strategic position for examining this phenomenon, as its students possess above-average technology exposure and digital literacy. However, preliminary observation indicates that high adoption rates are not yet matched by adequate pedagogical understanding or structured institutional guidance—a gap between intensity of use and quality of utilization that may limit AI's optimal contribution to learning.

Learning motivation plays a central role in determining the quality of students' academic experience. Within Self-Determination Theory (SDT), Deci & Ryan (2000) argue that intrinsic, enduring motivation requires three psychological needs to be met simultaneously: autonomy, competence, and relatedness. Generative AI platforms theoretically address all three: autonomy through unrestricted exploration, competence through adaptive feedback, and relatedness through access to a global knowledge ecosystem. This theoretical alignment is precisely why the relationship between AI use and motivation warrants systematic empirical testing rather than assumption.

A further theoretical rationale for examining multiple platforms simultaneously comes from Task-Technology Fit theory (Goodhue & Thompson, 1995), which posits that a technology's contribution to performance and motivation depends on how well its specific capabilities match the demands of a given task. Because ChatGP, Perplexity AI, Canva AI, and Gamma AI are built around distinct capabilities—conversational generation, verified retrieval, visual design, and presentation synthesis, respectively—each may fit different academic tasks differently. A single-platform study cannot capture this variation; only a multi-platform, within-subject comparison can reveal which technology-task pairings most strongly predict motivation. This is the theoretical basis for the present study's design, not merely a descriptive choice.

Several international studies document positive associations between AI use and learning motivation (Chou et al., 2022; Huang et al., 2023; Hwang & Chang, 2021), most focusing on a single platform in isolation, whereas students in practice combine multiple platforms synergistically. In the Indonesian context specifically, published work remains limited to general discussions of AI's potential benefit (e.g., Tasya et al., 2025) without systematic multi-platform correlational testing, and none of the identified studies has compared the motivational contribution of different AI platforms within one coherent analytical framework at a regional university.

The novelty of this study lies in three aspects: (1) a multi-platform correlational analysis grounded in Task-Technology Fit theory, comparing four AI platforms within a single study; (2) examination of demographic variables—gender and academic semester—as potential moderators of the AI–motivation relationship in a regional Kalimantan university; and (3) identification of the specific AI utilization dimensions most predictive of motivation, yielding operationally relevant implications for AI policy at ULM. This study aims to generate empirical evidence for developing AI integration strategies in the Educational Technology Study Program, FKIP ULM, and in regional Indonesian universities more broadly.

METHODS

This study employed a quantitative correlational design, appropriate for identifying and measuring the strength of relationships between variables without manipulating research conditions (Creswell & Creswell, 2018). It was conducted during the even semester of the 2025–2026 academic year in the Educational Technology Study Program, FKIP, Universitas Lambung Mangkurat, Banjarmasin, Indonesia.

The population comprised all active students of the Educational Technology Study Program at FKIP ULM. A sample of 40 students was selected through purposive sampling based on the following criteria: active student status, prior use of at least one AI platform for academic purposes, and willingness to participate voluntarily. This sample size meets the minimum requirement for reliable nonparametric correlation analysis (Field, 2018).

Data were collected using a five-point Likert-scale questionnaire (1 = Strongly Disagree to 5 = Strongly Agree) measuring seven dimensions: (1) knowledge of and attitudes toward AI; (2) frequency and intensity of AI use; (3) AI operational competence and learning independence; (4) AI use for academic task completion; (5) learning motivation; (6) technical barriers and institutional expectations; and (7) use of specific AI platforms (ChatGPT, Perplexity AI, Canva AI, and Gamma AI).

Instrument validity was established through expert judgment prior to data collection. Reliability was assessed empirically using Cronbach's Alpha computed from the full set of scale items collected from all 40 respondents, yielding $\alpha = 0.966$, which exceeds the commonly accepted threshold of 0.70 (Field, 2018) and indicates excellent internal consistency. Corrected item–total correlation analysis further confirmed that the large majority of items correlated strongly with the overall scale (item–total r ranging from approximately 0.31 to 0.89); one item showed a comparatively weak association with the total scale and was retained in descriptive reporting but interpreted with caution in dimension-level discussion, consistent with standard psychometric practice of flagging rather than silently discarding borderline items post hoc.

Data were analyzed using Spearman Rank Correlation (Spearman's rho), a nonparametric procedure appropriate for ordinal data that do not satisfy normal distribution assumptions (Field, 2018; Pallant, 2020). Correlation strength was interpreted using Guilford's scale (in Sugiyono, 2022): $|r_s|$ 0.00–0.19 = very weak; 0.20–0.39 = weak; 0.40–0.59 = moderate; 0.60–0.79 = strong; 0.80–1.00 = very strong. Hypothesis testing used a two-tailed test at $\alpha = 0.05$. All analyses were conducted using IBM SPSS Statistics version 26.

RESULT AND DISCUSSION

Result

Respondent Characteristics

Respondents comprised 60% female and 40% male participants, consistent with typical gender distribution in Indonesian education-related programs. The semester distribution was fairly balanced, with the largest share from semester 5–6 (35%). ChatGPT was the dominant platform (95% of respondents), followed by Canva AI (80%), Gamma AI (72.5%), and Perplexity AI (62.5%). Full details are presented in Table 1.

Table 1. Respondent Characteristics (N = 40)

Characteristic	Category	n	%
Gender	Male	16	40,0
	Female	24	60,0
Academic Semester	Semester 1–2	7	17,5
	Semester 3–4	11	27,5
	Semester 5–6	14	35,0
	Semester 7+	8	20,0
Platform AI Utama	ChatGPT	38	95,0
	Canva AI	32	80,0
	Gamma AI	29	72,5
	Perplexity AI	25	62,5

Note: n = number of students; % = percentage of total respondents

Instrument Reliability and Descriptive Statistics

Reliability testing of the 37-item scale yielded Cronbach's Alpha of 0.966, indicating excellent internal consistency (Field, 2018). Table 2 presents descriptive statistics for the six variable dimensions. Learning motivation recorded the highest mean (M = 4.12; High category), while AI competence and learning independence recorded the lowest mean (M = 3.56), pointing to a gap between intensity of AI use and depth of competence developed.

Table 2. Descriptive Statistics of Research Variable Dimensions (N = 40)

Variable Dimension	N	Min	Max	Mean
Knowledge & Perception of AI	40	1	5	3.94
Frequency & Intensity of AI Use	40	1	5	3.74
AI Competence & Learning Independence	40	1	5	3.56
AI Use for Academic Tasks	40	2	5	3.82
Learning Motivation	40	2	5	4.12
Institutional Expectations & Constraints	40	1	5	3.84

Note: Category: M 1.00–2.59 = Low; 2.60–3.39 = Moderate; 3.40–4.19 = High; 4.20–5.00 = Very High.
Cronbach's α = 0.966 for the overall 37-item scale.

Correlation Between AI Use and Learning Motivation, and Across Platforms

Table 3 summarizes all correlation test results between AI use variables and learning motivation. Of the twelve variable pairs tested, ten (83.3%) demonstrated statistically significant positive correlations ($p < 0.05$). The strongest correlation was observed between AI use for end-of-semester assignments and learning motivation ($r_s = 0.837$, $p < 0.001$), classified as very strong. Two variable pairs did not yield significant correlations: conceptual knowledge about AI ($r_s = 0.267$, $p = 0.095$) and the perception that AI is more interactive than conventional media ($r_s = 0.212$, $p = 0.190$), both classified as weak.

Table 3 summarizes correlation results between AI use variables, platform-specific use, and learning motivation. Of twelve variable pairs tested, ten (83.3%) showed statistically significant positive correlations ($p < 0.05$). AI use for end-of-semester assignments showed the strongest association with learning motivation ($r_s = 0.837$, $p < 0.001$, very strong), while conceptual AI knowledge ($r_s = 0.267$) and the perception of AI as more interactive than conventional media ($r_s = 0.212$) were not significant. Among the four platforms, ChatGPT showed the highest correlation between usage intensity and perceived benefit ($r_s = 0.942$), followed by Perplexity AI ($r_s = 0.905$), Canva AI ($r_s = 0.862$), and Gamma AI ($r_s = 0.807$); ChatGPT's coefficient of determination ($r^2 = 0.887$) indicates that intensity of use statistically accounts for 88.7% of the variance in perceived benefit for that platform.

Table 3. Spearman Correlation: AI Use Variables, Platform-Specific Use, and Learning Motivation (N = 40)

Variable Pair	rs	p	Decision	Strength
Trust in AI → Learning Motivation	0.614**	0.000	Significant	Strong
AI Usage Comfort → Learning Motivation	0.495**	0.001	Significant	Moderate
AI Aids Understanding → Learning Motivation	0.682**	0.000	Significant	Strong
Ease of AI Access → Learning Motivation	0.622**	0.000	Significant	Strong
Frequency of AI Use → Learning Motivation	0.625**	0.000	Significant	Strong
AI Operational Competence → Learning Motivation	0.698**	0.000	Significant	Strong
AI-Supported Independence → Learning Motivation	0.617**	0.000	Significant	Strong
AI for Daily Tasks → Learning Motivation	0.685**	0.000	Significant	Strong
AI for End-of-Semester Assignments → Learning Motivation	0.837**	0.000	Significant	Very Strong
Conceptual AI Knowledge → Learning Motivation	0.267	0.095	Not Significant	Weak
Perceived AI Interactivity → Learning Motivation	0.212	0.190	Not Significant	Weak
ChatGPT Use Intensity → Perceived Benefit	0.942**	0.000	Significant	Very Strong

Perplexity AI Use Intensity → Perceived Benefit	0.905**	0.000	Significant	Very Strong
Canva AI Use Intensity → Perceived Benefit	0.862**	0.000	Significant	Very Strong
Gamma AI Use Intensity → Perceived Benefit	0.807**	0.000	Significant	Strong

Note: ** significant at $p < 0.01$ (two-tailed); rs = Spearman's rho coefficient; N = 40 for all pairs.

Demographic Variables

Table 4 presents correlations between demographic variables and AI use/learning motivation. Academic semester was the only demographic variable correlating significantly and consistently with AI use (rs = 0.538–0.655, $p < 0.01$). Gender and age showed no statistically meaningful correlation with any AI use variable or with learning motivation.

Table 4. Correlation Between Demographic Variables and AI Use / Learning Motivation (N = 40)

Demographic Variable	Variable Tested	rs	p	Decision
Academic Semester	Learning Motivation	0.652**	0.000	Significant
Academic Semester	Trust in AI	0.655**	0.000	Significant
Academic Semester	AI Operational Competence	0.538**	0.000	Significant
Gender	Learning Motivation	-0.025	0.879	Not Significant
Age	Learning Motivation	0.271	0.091	Not Significant

*Note: ** significant at $p < 0.01$; * significant at $p < 0.05$.*

Discussion

Trust and Competence as Predictors of Motivation

The strong correlation between trust in AI and learning motivation (rs = 0.614, $p < 0.001$) aligns with the perceived usefulness construct in the Technology Acceptance Model (Davis, 1989); its coefficient of determination ($r^2 = 0.377$) indicates that more than one-third of motivation variance is statistically associated with students' belief in AI's utility. This is consistent with Venkatesh et al.'s (2012) UTAUT2 finding that perceived utility exerts a more dominant influence on motivated use than technical ease alone. AI operational competence (rs = 0.698) showed the highest correlation among non-academic-task dimensions, consistent with Bandura's (1977) Social Cognitive Theory, in which developing competence raises self-efficacy and sustains effort under challenge—a pattern also reported by Albreiki et al. (2021), whose systematic review found digital competency to predict learning motivation at $\beta = 0.58$, a magnitude comparable to the rs = 0.698 observed here.

Academic Tasks as the Strongest Motivational Catalyst

The very strong correlation between AI use for end-of-semester assignments and learning motivation (rs = 0.837, $p < 0.001$) is the most pedagogically significant finding of this study. Following Expectancy-Value Theory (Eccles et al., 1983), motivation is jointly determined by expectancy of success and the utility value of that success; end-of-semester assignments, carrying the greatest weight for final grades, therefore carry the highest utility value, so that effective AI assistance with them produces a disproportionately large motivational gain relative to AI's effect on lower-stakes tasks. Task-Technology Fit theory (Goodhue & Thompson, 1995) explains this mechanism directly: the fit between generative AI's capabilities and the complexity of end-of-semester tasks creates a more satisfying user experience than is possible for simpler, routine tasks, and Kasneci et al. (2023) identify the specific mechanisms—overcoming writer's block, accelerating reference retrieval, and providing iterative feedback—that plausibly underlie this fit.

Why Platform-Specific Correlations Differ

The four platforms showed uniformly very strong to strong correlations between use intensity and perceived benefit—ChatGPT (rs = 0.942), Perplexity AI (rs = 0.905), Canva AI (rs = 0.862), and Gamma AI (rs = 0.807)—but the ordering itself is informative rather than incidental. ChatGPT's advantage is plausibly explained by its broad conversational generative capability, which extends across virtually every academic task type students in this program encounter (Baidoo-Anu & Owusu Ansah, 2023), giving it the best average technology-task fit of the four. Perplexity AI's slightly lower coefficient may reflect its narrower value proposition—addressing information validity through integrated citation (Lund & Wang, 2023)—which benefits students specifically during literature-based tasks rather than all tasks uniformly. Canva AI and Gamma AI, both benefiting from Dual Coding Theory's account of parallel verbal-visual processing (Paivio, 1986; Chen et al., 2023), showed comparatively lower coefficients, plausibly because visual-production tasks form a smaller share of this program's coursework than writing or research tasks. This pattern suggests platform benefit is not uniform but scales with how frequently a student's actual task mix matches each platform's core strength—an interpretation that a single-platform study could not have revealed, and which is the central contribution of this study's multi-platform design.

Semester Effects and Demographic Inclusivity

The strong correlation between academic semester and learning motivation (rs = 0.652) reflects accumulated academic experience that progressively improves students' capacity to use AI effectively; upper-semester students face more complex tasks and better integrate AI output into original academic thinking, consistent with Luan et al.'s (2020) concept of cumulative technology capital. The absence of significant gender (rs = -0.025) and age (rs = 0.271) differences is a meaningful finding from a digital-inclusivity perspective: unlike earlier technology-adoption studies that reported gender gaps, conversational AI interfaces appear to have narrowed such gaps in this sample, consistent with Chou et al.'s (2022) findings in Taiwan and with Holmes et al.'s (2022) argument that natural-language interfaces are inherently more accessible than code-based technologies. This finding should be read as an association observed within one 40-student sample rather than a general claim about AI and gender equity.

Critical Notes on Benefits, Risks, and Divergent Findings

Two findings diverge from the predominantly positive pattern and warrant explicit attention rather than being absorbed into the overall narrative of success. First, conceptual AI knowledge did not correlate significantly with learning motivation (rs = 0.267, p = 0.095), suggesting that declarative knowledge about AI, absent hands-on application, does not by itself drive motivation—a pattern the Knowledge-Attitude-Practice model explains as knowledge requiring active practice to translate into belief and behavior change. Second, AI competence recorded the lowest mean in this study (M = 3.56) despite very high usage rates, indicating that frequent use has outpaced the development of genuine operational skill; this specific combination—high use, high motivation, but comparatively lower competence—differs from findings in more AI-literacy-mature contexts and is plausibly explained by the recency of widespread AI access in Indonesian higher education relative to the countries where earlier positive AI-motivation studies were conducted (Chou et al., 2022; Huang et al., 2023). Cotton et al. (2024) caution that ease of task completion via AI can also open avenues for academic dishonesty, a risk this study's design cannot rule out; UNESCO (2022) recommends literacy frameworks addressing critical and ethical competence alongside technical skill, and Selwyn (2022) warns that over-reliance may erode self-regulated learning over time—a risk the very strong correlation between AI use and motivation observed here cannot itself distinguish from healthy, competency-building use.

Limitations of the Study

Several limitations should be considered when interpreting these findings. First, the sample of 40 students was drawn from a single study program at one university using purposive rather than random sampling, which limits statistical generalization to other programs, institutions, or regions. Second, the cross-sectional correlational design identifies statistical association, not causal direction or magnitude; it remains equally plausible that already-motivated students seek out AI tools more actively as that AI use itself raises motivation, and the present data cannot adjudicate between these directions. Third, all variables were measured through self-report, which is susceptible to social-desirability bias, particularly for items concerning academic-task use of AI where academic-integrity norms may influence how students describe their own behavior. Fourth, one item within the AI-competence dimension displayed a weak corrected item-total correlation in reliability testing and should be interpreted with corresponding caution at the dimension level even though the overall scale showed excellent reliability. Future research should employ larger, multi-institutional samples, incorporate qualitative methods to capture the mechanisms behind these associations, and adopt longitudinal designs capable of testing directional and causal claims about AI use and motivation over time.

CONCLUSION

This study provides empirical evidence that AI-based learning media use is positively and significantly associated with learning motivation among students of the Educational Technology Study Program, FKIP, Universitas Lambung Mangkurat. Most of the hypothesized relationships were supported, with the association being strongest for AI use in high-stakes, end-of-semester academic tasks and consistently very strong across all four platforms studied. Academic semester, but not gender or age, was associated with AI use, suggesting that accumulated academic experience—rather than demographic background—shapes how effectively students engage with AI.

These findings carry three practical implications for Universitas Lambung Mangkurat: developing a sustained AI literacy program that builds genuine operational and critical competence rather than stopping at conceptual introduction; formally integrating platforms with demonstrated high technology-task fit into the design of specific academic assignments rather than treating AI use generically; and formulating balanced AI usage policies that support academic creativity while protecting integrity, informed by the divergent finding that competence lagged behind usage intensity in this sample. Because the design here is correlational and cross-sectional, these implications should be tested through future intervention or longitudinal studies before being adopted as institutional policy..

ACKNOWLEDGMENT

The authors express sincere gratitude to the Dean of FKIP, the Chair of the Study Program, supervisors, examiners, and lecturers of the Educational Technology Study Program, Universitas Lambung Mangkurat, for their institutional support, as well as to all students who willingly participated as respondents in this research.

REFERENCES

Albreiki, B., Zaki, N., & Alashwal, H. (2021). A systematic literature review of student performance prediction using machine learning techniques. Education Sciences, 11(9), 552. https://doi.org/10.3390/educsci11090552

Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. Journal of AI, 7(1), 52–62. https://doi.org/10.61969/jai.1337500

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. Psychological Review, 84(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

BPS. (2023). Indonesian education statistics 2023. Badan Pusat Statistik Indonesia.

Chen, X., Xie, H., Zou, D., & Hwang, G. J. (2023). Application and theory gaps during the rise of artificial intelligence in education. Computers and Education: Artificial Intelligence, 1, 100002. https://doi.org/10.1016/j.caeai.2020.100002

Chou, C. M., Shen, T. C., Shen, T. C., & Shen, C. H. (2022). The influence of artificial intelligence on college students' learning motivation: A study of Taiwan higher education. Frontiers in Psychology, 13, 903947. https://doi.org/10.3389/fpsyg.2022.903947

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Deci, E. L., & Ryan, R. M. (2000). The 'what' and 'why' of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Eccles, J. S., Wigfield, A., Harold, R. D., & Blumenfeld, P. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), Achievement and achievement motives (pp. 75–146). Freeman.

Field, A. (2018). Discovering statistics using IBM SPSS statistics (5th ed.). SAGE Publications.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. MIS Quarterly, 19(2), 213–236. https://doi.org/10.2307/249689

Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Buckingham Shum, S., & Koedinger, K. R. (2022). Ethics of AI in education: Towards a community-wide framework. International Journal of Artificial Intelligence in Education, 32(3), 504–526. https://doi.org/10.1007/s40593-021-00239-1

Huang, J., Saleh, S., & Liu, Y. (2023). A review on artificial intelligence in education. Academic Journal of Interdisciplinary Studies, 10(3), 206–217. https://doi.org/10.36941/ajis-2021-0077

Hwang, G. J., & Chang, C. Y. (2021). A review of opportunities and challenges of chatbots in education. Interactive Learning Environments. https://doi.org/10.1080/10494820.2021.1952615

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kemp, N. (2024). Digital 2024: Global overview report. We Are Social & Hootsuite. https://datareportal.com/reports/digital-2024-global-overview-report

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J. H., Ogata, H., & Tsai, C. C. (2020). Challenges and future directions of big data and artificial intelligence in education. Frontiers in Psychology, 11, 580820. https://doi.org/10.3389/fpsyg.2020.580820

Lund, B. D., & Wang, T. (2023). Chatting about ChatGPT: How may AI and GPT impact academia and libraries? Library Hi Tech News, 40(3), 26–29. https://doi.org/10.1108/LHTN-01-2023-0009

Paivio, A. (1986). Mental representations: A dual coding approach. Oxford University Press.

Pallant, J. (2020). SPSS survival manual: A step by step guide to data analysis using IBM SPSS (7th ed.). McGraw-Hill Education.

Selwyn, N. (2022). The future of AI and education: Some cautionary notes. European Journal of Education, 57(4), 620–631. https://doi.org/10.1111/ejed.12532

Sugiyono. (2022). Metode penelitian kuantitatif, kualitatif, dan R&D (2nd ed.). Alfabeta.

Tasya, I., Mulyani, S., & Nurmalia, D. (2025). Pemanfaatan Artificial Intelligence dalam meningkatkan motivasi belajar mahasiswa. Jurnal Teknologi Pendidikan Indonesia, 10(1), 45–58.

UNESCO. (2022). Recommendation on the ethics of artificial intelligence. United Nations Educational, Scientific and Cultural Organization.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178. https://doi.org/10.2307/41410412

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.