Journal of Applied Education Science
Open Access: https://doi.org/10.65897/jaes.v1.i1.105
Vol. 1, Issue 1, 2026, pp. 8–13

Correlates of University Students' AI Usage Intention for Learning: A Secondary Analysis of Indonesian Students

Windi Widyastuti[1], Kukuh Rokhman Hidayat[2]
[1]Politeknik Al Islam Bandung, Indonesia
[2]UIN Siber Syekh Nurjati Cirebon, Indonesia
[1]windiwidyastuti@gmail.com
[2]kukuhrhidayat@gmail.com

Article History:
Received: July 21, 2026
Revised: July 24, 2026
Accepted: July 25, 2026
Published: July 25, 2026

Corresponding Author:
Windi Widyastuti
windiwidyastuti@gmail.com

Copyright © 2026 The Author(s).
Published by GWS Tech Solution
This is an open-access article under the CC BY 4.0 International License.

ABSTRACT

Artificial intelligence (AI) is now widely used in higher education, but adoption indicators do not by themselves show which factors are uniquely associated with students' intention to use AI for academic work. This study reanalysed publicly available aggregate results from a 2024 survey of 535 students at 152 Indonesian higher education institutions in 20 provinces. The source reported item means, AI-tool frequencies, and a correlation matrix for performance expectations, challenges, attitudes, perceptions, and a construct originally labelled motivational intention. For clarity, the present article reports this outcome as AI usage intention without changing its items, scores, or correlations. Equal-weighted construct means were reconstructed from the published item means, and standardized multiple regression was derived from the published correlation matrix. The four-predictor model accounted for approximately 55.4% of the variance in AI usage intention. Attitudes had the strongest unique association (β = .361), followed by perceptions (β = .277) and performance expectations (β = .242), all p < .001. Challenges correlated with usage intention at the bivariate level (r = .310) but made no unique contribution after overlap with the other constructs was considered (β = .012, p = .720). ChatGPT was the most frequently reported primary tool (47.5%). The findings represent statistical associations rather than causal effects. Universities should combine access with discipline-specific AI literacy, transparent assessment rules, output verification, and learning activities that preserve student judgement.

Keywords: artificial intelligence, higher education, usage intention, technology adoption

ABSTRAK

Kecerdasan buatan (AI) telah digunakan secara luas dalam pendidikan tinggi, tetapi indikator adopsi belum menunjukkan faktor mana yang secara unik berkaitan dengan niat mahasiswa menggunakan AI untuk kegiatan akademik. Penelitian ini menganalisis kembali hasil agregat yang tersedia secara publik dari survei tahun 2024 terhadap 535 mahasiswa pada 152 perguruan tinggi di 20 provinsi Indonesia. Sumber data melaporkan rerata butir, frekuensi alat AI, serta matriks korelasi untuk ekspektasi kinerja, tantangan, sikap, persepsi, dan konstruk yang pada sumber disebut motivational intention. Untuk memperjelas istilah, artikel ini menggunakan sebutan niat penggunaan AI tanpa mengubah butir, skor, atau korelasi konstruk tersebut. Rerata konstruk berbobot sama direkonstruksi dari rerata butir yang dipublikasikan, sedangkan regresi berganda terstandar diturunkan dari matriks korelasi. Model dengan empat prediktor menjelaskan sekitar 55,4% variasi niat penggunaan AI. Sikap memiliki hubungan unik terkuat (β = 0,361), diikuti persepsi (β = 0,277) dan ekspektasi kinerja (β = 0,242), seluruhnya p < 0,001. Tantangan berkorelasi dengan niat penggunaan pada tingkat bivariat (r = 0,310), tetapi tidak memberikan kontribusi unik setelah tumpang tindih dengan konstruk lain diperhitungkan (β = 0,012, p = 0,720). ChatGPT merupakan alat utama yang paling sering dilaporkan (47,5%). Temuan menunjukkan hubungan statistik, bukan pengaruh kausal. Perguruan tinggi perlu memadukan akses dengan literasi AI berbasis disiplin, aturan asesmen yang transparan, verifikasi keluaran, dan aktivitas belajar yang mempertahankan penilaian mahasiswa.

Kata kunci: *kecerdasan buatan, niat penggunaan, pendidikan tinggi, adopsi teknologi*

1. INTRODUCTION

Artificial intelligence (AI) has moved from a specialised technical domain into routine academic practice. University students use conversational systems, search assistants, translation tools, image generators, presentation applications, and automated feedback systems for tasks ranging from brainstorming and explanation to drafting and revision. These uses can expand access to feedback and support, but they also raise concerns about inaccurate output, bias, privacy, overreliance, authorship, and academic integrity [3], [8], [17], [20], [24]. The practical question for higher education is therefore not simply whether students use AI, but which beliefs are associated with their intention to continue using it and how institutions can direct that intention toward educationally defensible practice.

Technology-adoption theory provides a useful explanatory frame. The Technology Acceptance Model proposes that perceived usefulness and perceived ease of use shape attitude and behavioural intention [9]. The Unified Theory of Acceptance and Use of Technology places performance expectancy, effort expectancy, social influence, and facilitating conditions at the centre of adoption [21], while UTAUT2 extends the model through motivational and habitual factors [22]. Social cognitive theory further suggests that efficacy beliefs, observed consequences, and prior experience contribute to technology-related behaviour [1]. In AI-mediated learning, however, adoption also depends on whether students regard AI output as trustworthy, academically legitimate, ethically acceptable, and compatible with their own intellectual responsibility [5]-[7], [15], [25].

Recent research portrays students as interested but not uncritical. Reported benefits include productivity, idea development, explanation, language support, and rapid feedback, whereas recurring concerns include misinformation, dependency, privacy, fairness, and unclear institutional expectations [6]-[8], [18], [23]. AI literacy and self-efficacy affect whether students can interrogate outputs rather than merely accept them [2], [4], [10]-[12], [14], [16], [19]. These findings imply that access and frequency of use are incomplete measures of meaningful educational adoption. A student can intend to use AI frequently without using it in ways that improve comprehension, transfer, or responsible authorship.

Evidence from Indonesia is growing, but opportunities for transparent secondary analysis remain underused. Luthfi et al. published a dataset describing AI use among 535 students from 152 higher education institutions in 20 provinces, including performance expectations, challenges, attitudes, perceptions, and a construct labelled motivational intention in the source [13]. For clarity, the present study reports this outcome as AI usage intention. The source article provided descriptive statistics and a correlation matrix. Because predictors can share substantial variance, bivariate correlations alone cannot show which constructs retain a unique statistical association with usage intention after the others are considered simultaneously. Reconstructing a standardized regression model from the published matrix provides an economical and reproducible way to address that question without claiming access to respondent-level records.

This study had three objectives: (1) to describe the sample, reported AI tools, and adoption constructs, (2) to examine the direction and magnitude of relationships among performance expectations, challenges, attitudes, perceptions, and AI usage intention, and (3) to estimate the unique standardized association of each predictor with AI usage intention. The contribution is methodological as well as practical. It demonstrates a transparent aggregate-data reanalysis while translating the results into bounded recommendations for AI literacy, course design, assessment, and institutional governance.

2. METHOD

2.1. Research Design

The study used a quantitative secondary-analysis design based exclusively on publicly reported aggregate statistics. No respondent-level records were downloaded, reconstructed, or simulated. The analytical inputs were the sample profile, AI-tool frequencies, item means, and interconstruct Pearson correlation matrix reported in the source data article and repository [13]. Correlation-matrix regression was selected because it estimates the standardized contribution of each predictor while making the evidential limits of the available data explicit.

2.2. Data Source and Sample

The source survey comprised 535 students from 152 higher education institutions in 20 Indonesian provinces. Online data collection was conducted through Google Forms between August and October 2024 [13]. The sample included 369 women (69.0%) and 166 men (31.0%), 474 participants (88.6%) studied at public institutions and 61 (11.4%) at private institutions. Undergraduate students represented 83.0% of the sample, and diploma students represented 17.0%. Social sciences and education were the largest fields. Although the source describes the sampling as simple random sampling, the public article does not report a complete sampling frame or response rate, the present study therefore treats the sample as broad and multi-institutional, not nationally representative.

2.3. Measures and Data Extraction

The source questionnaire used a four-point Likert format ranging from 1 (strongly disagree) to 4 (strongly agree). Five constructs were reported: performance expectations (20 items), challenges in using AI (4 items), attitudes toward AI use (5 items), perceptions of AI use (5 items), and motivational intention to use AI (5 items) [13]. To use a clearer and more common term in technology-adoption research, the present article refers to the fifth construct as AI usage intention. This change is terminological only and does not alter the original items, scores, or correlations. AI usage intention should not be interpreted as observed behaviour or verified learning gain.

For descriptive purposes, an equal-weighted construct mean was calculated as the arithmetic average of the published item means. Because every item was reported with n = 535, this value is equivalent to the mean of an equally weighted item composite under complete data. However, the composite variance, standard deviation, measurement model, and subgroup distributions cannot be reconstructed from item means alone. Frequencies and the correlation matrix were independently transcribed twice, checked against the source tables, and verified for internal consistency, symmetry, and positive definiteness before analysis.

2.4. Data Analysis and Reproducibility

Frequencies, percentages, equal-weighted construct means, item-mean ranges, and differences from the scale midpoint (2.50) were calculated descriptively. Pearson coefficients were interpreted as zero-order associations. Standardized multiple-regression coefficients were reconstructed as $\beta = RXX^{-1}rXY$, where RXX is the predictor correlation matrix and rXY is the vector of predictor-outcome correlations. Model fit was calculated as $R^2 = \beta' rXY$. Approximate standard errors, t statistics, 95% confidence intervals, adjusted R^2, the omnibus F statistic, and variance inflation factors were derived using n = 535, four predictors, and 530 residual degrees of freedom.

The calculations were reproduced in Python 3.13 using NumPy 2.3.5 and SciPy 1.17.0. Because the published correlations were rounded to three decimal places, regression coefficients and inferential statistics should be read as close reconstructions rather than exact substitutes for analysis of the raw data. The study used only public, anonymised aggregate statistics, did not access personal identifiers, and involved no new contact with human participants. The underlying dataset is available from Mendeley Data under DOI 10.17632/b89t4x2c2y.1 [13].

3. RESULTS AND DISCUSSION

3.1. Results

Table 1. Characteristics of the Source Sample

Dimension	Category	n	%
Gender	Women	369	69.0
	Men	166	31.0
Institution type	Public institution	474	88.6
	Private institution	61	11.4
Education level	Undergraduate (S1)	444	83.0
	Diploma (D3)	91	17.0
Largest study fields	Social sciences	197	36.8
	Education	147	27.5
	Engineering	50	9.3
	Economics	48	9.0

The sample covered a large number of institutions and provinces but was not demographically balanced. Women, public-institution students, undergraduates, and students in social sciences and education were overrepresented. The results should therefore be interpreted as patterns within the available sample rather than population estimates for all Indonesian university students.

Table 2. Primary Artificial Intelligence Tools Reported by Students

Tool category	n	%
ChatGPT	254	47.5
Canva AI	81	15.1
Perplexity.AI	71	13.3
Other tools	58	10.8
DeepL	23	4.3
Bing	18	3.4
DALL-E	15	2.8
Eduten, Gamma, Tome.app, and Shutterstock AI combined	15	2.8

ChatGPT was the most frequently selected primary tool, accounting for 47.5% of responses. However, 52.5% of respondents selected another tool, showing that the student AI environment also included visual-design, search, translation, image-generation, presentation, and subject-specific applications. The source item measured a primary tool rather than the full number of tools used by each student.

Table 3. Equal-Weighted Construct Means Reconstructed from Published Item Means

Construct	Items	Mean	Item-mean range	Difference from midpoint
Performance expectations	20	3.046	2.83-3.18	+0.546
Challenges in using AI	4	2.460	2.30-2.78	−0.040
Attitudes toward AI use	5	2.862	2.62-3.01	+0.362
Perceptions of AI use	5	2.670	1.99-3.17	+0.170
AI usage intention	5	2.744	2.48-3.00	+0.244

Performance expectations had the highest reconstructed mean (3.046), followed by attitudes (2.862), AI usage intention (2.744), and perceptions (2.670). Challenges were close to the midpoint (2.460). These descriptive results indicate favourable expectations and attitudes on average, but they do not establish prevalence, causation, or educational effectiveness.

Table 4. Pearson Correlations among Artificial Intelligence Adoption Constructs

Construct	1	2	3	4	5
1. Performance expectations	1.000				
2. Challenges in using AI	.236	1.000			
3. Attitudes toward AI use	.570	.317	1.000		
4. Perceptions of AI use	.475	.458	.590	1.000	
5. AI usage intention	.582	.310	.666	.610	1.000

AI usage intention was most strongly correlated with attitudes (r = .666), followed by perceptions (r = .610) and performance expectations (r = .582). Challenges had a smaller positive correlation with usage intention (r = .310). Correlations among predictors ranged from .236 to .590, showing meaningful overlap but no indication of severe redundancy.

Table 5. Reconstructed Standardized Multiple Regression Predicting AI Usage Intention

Predictor	β	SE	t	p	95% CI	VIF
Performance expectations	0.242	0.036	6.70	< .001	[0.171, 0.313]	1.55
Challenges in using AI	0.012	0.033	0.36	.720	[−0.053, 0.076]	1.27
Attitudes toward AI use	0.361	0.039	9.16	< .001	[0.284, 0.439]	1.85
Perceptions of AI use	0.277	0.039	7.06	< .001	[0.200, 0.354]	1.82

The four-predictor model accounted for approximately 55.4% of the variance in AI usage intention. Attitudes showed the strongest unique standardized association (β = .361), followed by perceptions (β = .277) and performance expectations (β = .242). Challenges did not contribute unique explained variance after the shared relationships among predictors were controlled (β = .012, p = .720). All VIF values were below 2, indicating that multicollinearity was not materially distorting the reconstructed model.

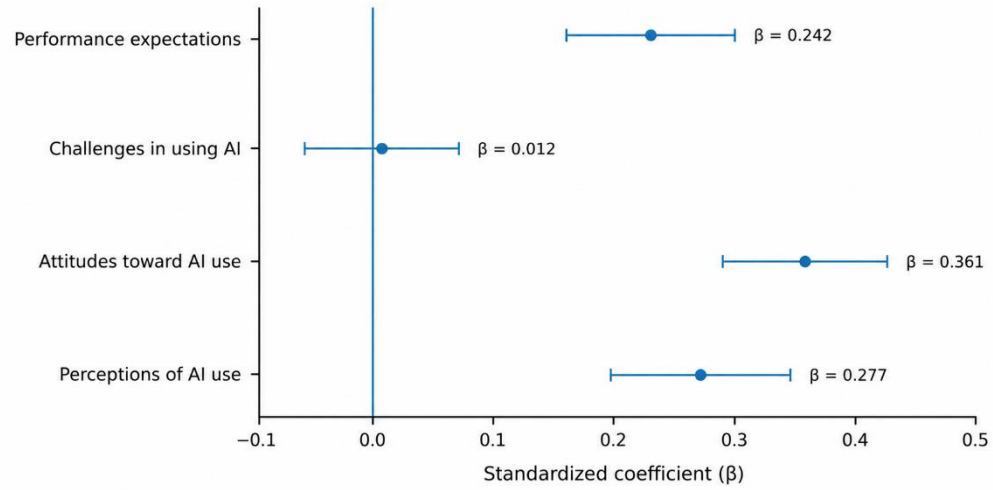


Figure 1. Reconstructed standardized coefficients and 95% confidence intervals for AI usage intention

3.2. Discussion

3.2.1. Attitudes Show the Strongest Unique Association

The principal result is that attitudes retained the strongest unique association with AI usage intention after the other constructs were included. This pattern is consistent with technology-acceptance theory, which positions attitude as an evaluative link between beliefs about a system and intention to use it [9], [21]. It also accords with higher education research showing that perceived value, confidence, acceptance, and ethical appraisal shape students' willingness to engage with generative AI [2], [5], [6], [25]. The finding should not be read as evidence that a positive attitude causes continued use. Cross-sectional correlations cannot establish temporal order, and the reconstructed model cannot rule out reciprocal relationships or unmeasured factors.

For practice, the result suggests that institutions should shape informed attitudes through experience rather than promotion. Students are likely to evaluate AI more favourably when activities reveal a genuine academic purpose, require verification, and preserve human judgement. Conversely, inaccurate outputs, unclear rules, or activities that reward superficial completion may produce either rejection or uncritical dependence. The desirable target is not enthusiasm alone but a critically positive orientation supported by evidence and responsibility.

3.2.2. Perceptions and Performance Expectations Remain Important

Perceptions of AI use and performance expectations also retained unique associations with AI usage intention. Usage intention was therefore related not only to general evaluation but also to whether AI was perceived as appropriate and capable of supporting academic performance. This pattern is compatible with perceived usefulness in the Technology

Acceptance Model and performance expectancy in UTAUT [9], [21]. Related research has similarly linked usefulness, expected benefit, institutional support, and expectancy-value beliefs with AI adoption and learning intentions [7], [8], [14], [15], [19].

Universities can make academic value observable through discipline-specific use cases. In writing, AI might generate counterarguments that students must evaluate and revise. In programming, it may support debugging followed by an explanation of the underlying logic. In teacher education, students can compare lesson plans, identify bias, and justify modifications. In each case, the assessment should reward disciplinary judgement and learning evidence rather than the mere production of fluent output.

3.2.3. Challenges Correlate with Usage Intention but Add No Unique Variance

Challenges in using AI correlated positively with AI usage intention at the bivariate level but became negligible in the multivariable model. This does not show that barriers are unimportant. It indicates that the challenge construct contributed little additional information once attitudes, perceptions, and performance expectations were considered together. One plausible interpretation is an exposure effect: students who use AI more often may both intend to continue and become more aware of limitations. Another is conceptual overlap between challenge items and broader perceptions. Aggregate data cannot distinguish these explanations.

The result cautions against treating technical training as the whole adoption strategy. Access, troubleshooting, and platform guidance remain necessary, but responsible educational use also requires output evaluation, source checking, privacy awareness, and clear academic boundaries. AI literacy frameworks consistently define competence as understanding, critical evaluation, ethical judgement, and effective use rather than operational skill alone [4], [10]-[12], [16].

3.2.4. From Usage Intention to Responsible Educational Use

AI usage intention is not a learning outcome. Students may intend to use AI because it saves time, generates polished language, or reduces difficult cognitive work. Accordingly, institutional strategy should not pursue the highest possible adoption rate. Reviews and policy guidance emphasise transparent disclosure, process-based assessment, source verification, human oversight, privacy protection, and proportional governance [3], [17], [18], [20], [23], [24]. The observed associations are most useful when interpreted within that broader educational framework.

Table 6. Applied Recommendations for Responsible Artificial Intelligence Adoption

Domain	Recommended action	Minimum evaluation indicator
Curriculum	Embed discipline-specific AI literacy and critical evaluation in programme outcomes.	Verified output quality, ability to explain and challenge AI responses.
Teaching	Use AI for guided comparison, feedback, simulation, and revision rather than answer substitution.	Improvement between drafts, conceptual explanation, transfer to new tasks.
Assessment	Require process evidence, disclosure, source verification, and selected oral defence.	Transparent contribution, fewer unsupported claims, demonstrable authorship.
Student support	Combine technical access with pedagogical coaching, accessibility support, and ethical guidance.	Verification confidence, responsible-use knowledge, equitable participation.
Governance	Adopt risk-based rules for privacy, data sensitivity, approved tools, and accountability.	Policy clarity, privacy incidents, consistent handling of AI-assisted work.

3.2.5. Limitations and Future Research

This study has six limitations. First, the analysis used aggregate statistics rather than respondent-level data. Second, the correlations were published to three decimal places, so the reconstructed coefficients, standard errors, confidence intervals, and p values are approximate. Third, the study could not test measurement validity, reliability at the construct level, missing-data patterns, nonlinearity, interactions, or measurement invariance. Fourth, the source sample was broad but not demonstrably representative because a complete sampling frame and response rate were not reported. Fifth, all constructs were self-reported and cross-sectional, common-method variance and reverse direction are possible. Sixth, AI usage intention is not equivalent to actual AI use, learning quality, or academic achievement.

Future secondary analyses should use the public respondent-level dataset, preregister variable construction, validate the measurement model, and compare fields of study, institution types, and educational levels. Longitudinal and intervention research is also needed to determine whether AI literacy, transparent assessment rules, or discipline-specific learning designs change actual behaviour and learning outcomes. Studies should connect adoption measures with verifiable indicators such as output accuracy, source quality, conceptual explanation, revision quality, transfer, and responsible-use practices.

4. CONCLUSION

This secondary analysis found that attitudes, perceptions, and performance expectations were each uniquely associated with Indonesian university students' AI usage intention for learning. The reconstructed four-predictor model accounted for approximately 55.4% of the variance in usage intention, with attitudes showing the strongest unique association. Challenges were positively correlated with usage intention but did not add unique explained variance after overlap with the other constructs was considered.

The findings do not establish causal effects, national prevalence, actual AI behaviour, or improved learning. Their practical value lies in showing that responsible adoption cannot be reduced to access and technical training. Higher

education institutions should make academic value visible through authentic disciplinary tasks, develop critical AI literacy, require verification and disclosure, and establish clear assessment and data-governance expectations. The institutional objective should be competent, transparent, and educationally productive AI use, not adoption for its own sake.

REFERENCES

[1] A. Bandura, Social Foundations of Thought and Action: A Social Cognitive Theory. Englewood Cliffs, NJ, USA: Prentice-Hall, 1986.

[2] A. Bewersdorff, M. Hornberger, C. Nerdel, and D. S. Schiff, "AI advocates and cautious critics: How AI attitudes, AI interest, use of AI, and AI literacy build university students' AI self-efficacy," Computers and Education: Artificial Intelligence, vol. 8, Art. no. 100340, 2025, doi: 10.1016/j.caeai.2024.100340.

[3] K. Bittle and O. El-Gayar, "Generative AI and academic integrity in higher education: A systematic review and research agenda," Information, vol. 16, no. 4, Art. no. 296, 2025, doi: 10.3390/info16040296.

[4] A. Carolus, M. Koch, J. Straka, M. Latoschik, and C. Wienrich, "MAILS—Meta AI literacy scale: Development and testing of an AI literacy questionnaire based on well-founded competency models and psychological change- and meta-competencies," Computers in Human Behavior: Artificial Humans, vol. 1, no. 2, Art. no. 100014, 2023, doi: 10.1016/j.chbah.2023.100014.

[5] C. K. Y. Chan, "A comprehensive AI policy education framework for university teaching and learning," International Journal of Educational Technology in Higher Education, vol. 20, Art. no. 38, 2023, doi: 10.1186/s41239-023-00408-3.

[6] C. K. Y. Chan and W. Hu, "Students' voices on generative AI: Perceptions, benefits, and challenges in higher education," International Journal of Educational Technology in Higher Education, vol. 20, Art. no. 43, 2023, doi: 10.1186/s41239-023-00411-8.

[7] C. K. Y. Chan and W. Zhou, "Deconstructing student perceptions of generative AI: An expectancy-value theory instrument," Smart Learning Environments, vol. 10, Art. no. 35, 2023, doi: 10.1186/s40561-023-00284-4.

[8] H. Crompton and D. Burke, "Artificial intelligence in higher education: The state of the field," International Journal of Educational Technology in Higher Education, vol. 20, Art. no. 22, 2023, doi: 10.1186/s41239-023-00392-8.

[9] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, vol. 13, no. 3, pp. 319-340, 1989, doi: 10.2307/249008.

[10] M. Hornberger, A. Bewersdorff, and C. Nerdel, "What do university students know about artificial intelligence? Development and validation of an AI literacy test," Computers and Education: Artificial Intelligence, vol. 5, Art. no. 100165, 2023, doi: 10.1016/j.caeai.2023.100165.

[11] M. C. Laupichler, A. Aster, J. Schirch, and T. Raupach, "Artificial intelligence literacy in higher and adult education: A scoping literature review," Computers and Education: Artificial Intelligence, vol. 3, Art. no. 100101, 2022, doi: 10.1016/j.caeai.2022.100101.

[12] D. Long and B. Magerko, "What is AI literacy? Competencies and design considerations," in Proc. 2020 CHI Conf. Human Factors in Computing Systems, 2020, pp. 1-16, doi: 10.1145/3313831.3376727.

[13] Z. F. Luthfi, W. H. Prasetiyo, B. I. Sari, A. Waldi, and A. Muttaqiin, "Dataset of AI adoption usage, expectations, attitudes, perceptions, and motivations for learning in higher education," Data in Brief, vol. 63, Art. no. 112106, 2025, doi: 10.1016/j.dib.2025.112106.

[14] H. M. H. Mansoor, A. Bawazir, M. A. Alsabri, A. Alharbi, and A. H. Okela, "Artificial intelligence literacy among university students—A comparative transnational survey," Frontiers in Communication, vol. 9, Art. no. 1478476, 2024, doi: 10.3389/fcomm.2024.1478476.

[15] A. M. Musyaffi, M. A. Adha, H. Mukhibad, and M. C. Oli, "Improving students' openness to artificial intelligence through risk awareness and digital literacy: Evidence from a developing country," Social Sciences & Humanities Open, vol. 10, Art. no. 101168, 2024, doi: 10.1016/j.ssaho.2024.101168.

[16] D. T. K. Ng, J. K. L. Leung, S. K. W. Chu, and M. S. Qiao, "Conceptualizing AI literacy: An exploratory review," Computers and Education: Artificial Intelligence, vol. 2, Art. no. 100041, 2021, doi: 10.1016/j.caeai.2021.100041.

[17] OECD, OECD Digital Education Outlook 2026: Exploring Effective Uses of Generative AI in Education. Paris, France: OECD Publishing, 2026, doi: 10.1787/062a7394-en.

[18] Y. Qian, "Pedagogical applications of generative AI in higher education: A systematic review of the field," TechTrends, vol. 69, pp. 1105-1120, 2025, doi: 10.1007/s11528-025-01100-1.

[19] Y. Shen and W. Cui, "Perceived support and AI literacy: The mediating role of psychological needs satisfaction," Frontiers in Psychology, vol. 15, Art. no. 1415248, 2024, doi: 10.3389/fpsyg.2024.1415248.

[20] UNESCO, Guidance for Generative AI in Education and Research. Paris, France: UNESCO, 2023.

[21] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," MIS Quarterly, vol. 27, no. 3, pp. 425-478, 2003, doi: 10.2307/30036540.

[22] V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology," MIS Quarterly, vol. 36, no. 1, pp. 157-178, 2012, doi: 10.2307/41410412.

[23] F. Wu, Y. Dang, and M. Li, "A systematic review of responses, attitudes, and utilization behaviors on generative AI for teaching and learning in higher education," Behavioral Sciences, vol. 15, no. 4, Art. no. 467, 2025, doi: 10.3390/bs15040467.

[24] Q. Xia, X. Weng, F. Ouyang, T.-J. Lin, and T. K. F. Chiu, "A scoping review on how generative artificial intelligence transforms assessment in higher education," International Journal of Educational Technology in Higher Education, vol. 21, Art. no. 40, 2024, doi: 10.1186/s41239-024-00468-z.

[25] W. Zhu, L. Huang, X. Zhou, X. Li, G. Shi, J. Ying, and C. Wang, "Could AI ethical anxiety, perceived ethical risks and ethical awareness about AI influence university students' use of generative AI products? An ethical perspective," International Journal of Human-Computer Interaction, vol. 41, no. 1, pp. 742-764, 2025, doi: 10.1080/10447318.2024.2323277.