Engaging with AI in Assessment: Insights from Undergraduate Hospitality Students

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Abstract

As part one of a mixed-methods project, this quantitative study examined how students' perceptions of artificial intelligence (AI) in education influence perceived learning outcomes in an AI-supported assessment. A post-task survey was completed by 82 bachelor students measuring three facts of AI perception in education: affective, behavioural, and cognitive, and five domains of perceived learning: cognitive understanding, technical proficiency, critical evaluation, ethical awareness, and metacognitive reflection. Multiple regressions indicated that perceptions of AI significantly predicted overall perceived learning. The affective facet was the strongest and most consistent predictor, associated with cognitive understanding, technical proficiency, and critical evaluation, whereas behavioural and cognitive facets were non-significant. Findings suggest that positive feelings toward AI play a central role in shaping students' sense of learning. Pedagogical designs should therefore foster constructive affect alongside technical and critical engagement.

Key Words
AI, assessment, perceived learning, critical thinking, hospitality and tourism education

Track
Educational innovations

Focus of the Paper
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Introduction

Artificial intelligence (AI), and in particular generative AI, is reshaping the way students approach academic tasks. While educators have expressed concerns about the cognitive debt which can incur through AI use (Kosmyna et al., 2025) senior and graduate students are using AI to manage complex tasks and enhance productivity (Singer-Freeman et al., 2025). In hospitality and tourism education, where digital fluency is now considered a core graduate skill (Silva et al., 2025), embedding AI meaningfully into curricula is both timely and essential. Recent frameworks, such as Perkins et al.'s (2024) AI Assessment Scale, advocate moving beyond prohibition toward structured engagement, positioning AI as a co-creator in assessment. Yet limited research has explored how students experience learning through assessments that explicitly integrate AI, or how different dimensions of AI perception in education: cognitive, affective, and behavioural, influence perceived learning. This study, the first in a two-part, mixed methods project, seeks to provide quantifiable data which addresses this gap. Using a cross-sectional quantitative design, the study tests the extent to which domain-specific perceptions of AI in education predict perception of learning from a specific AI-supported assessment.

Reviewing the literature

Omnipresence of of Artificial intelligence

Through devices such as smart speakers, navigation apps, suggestions for playlists and potential purchases, humans' reliance on artificial intelligence (AI) has grown hugely this decade. Even more spectacular has been the rise of the acceptance of Generative AI in everyday life for answering questions, offering advice, writing content, generating images and videos, and building conversational agents (Open AI, 2025) with McKinsey suggesting approximately 11% of respondents of adults in the US actively using it either daily or weekly (Guadamuz, 2025). This digital transformation will continue in the workplace with AI predicted to be as transformative as the steam engine (McKinsey & Company, 2025). It is to be borne in mind that while the steam engine engendered huge, rapid and economically impactful changes to humans worldwide, it also began the deregulation of our climate (Perlin, 2023). If the analogy is to be made to this invention, then perhaps the future it is taking us to is one that cannot, at the present time, be foreseen.

Artificial intelligence in education

Echoing the positive reception of generative AI in society, research shows that its application in education increases student engagement and offers a more personalized, flexible, and adaptive learning experience (Caucheteux et al., 2024; Putri & Sain, 2025), particularly for international students (T. Wang et al., 2023). Unsurprisingly, students with lower confidence in academic writing are more likely to use generative AI tools, whereas more confident students are less supportive of such use (Johnston et al., 2024). Educators also recognise generative AI's benefits for routine professional tasks, with 60% reporting its use (Hamilton, 2024). However, Barrett and Pack (2023) note that many educators view student use less favourably, fearing it fosters superficial learning and undermines the development of social and critical thinking skills (Mogavi et al., 2024). Ivanov (2023) offers a thorough examination of generative AI's impact on ethics, creativity, and critical thinking. In response to such concerns, some educators have attempted to ban these tools (Perkins et al., 2024), though such efforts appear futile as student use increases and faculty remain unsure how to respond (Barrett & Pack, 2023).

Perkins et al. (2024) address this issue in their informative work, introducing a five-level scale of AI use in assessments (see Figure 1). Their scale presents involvement of AI in assessments ranging from level 1 where no AI is allowed to be used in the assessment, to level 5 where AI and the student co-create the work to be assessed, in a collaborative manner, perhaps reflecting the expectations of the workplace. Initial educator resistance and potentially fear of AI led to educators trying to ban the use of AI in assessed work but, possibly in a bid to promote the sort of responsible AI use Abuzar and Mutholfin (2025) advocate, the higher the scale, the more AI is used and engaged with in the production of the work to be assessed. Such an emphasis on encouraging learners to critically engage with AI through their learning rather than banning its use aligns with Delcker et al. (2024)'s perspective.

Figure 1 Perkins et al. (2024)'s AI assessment scale

Scale Levels and Descriptions

1	**NO AI**	The assessment is completed entirely without AI assistance. This level ensures that students rely solely on their knowledge, understanding, and skills. **AI must not be used at any point during the assessment.**
2	**AI-ASSISTED IDEA GENERATION AND STRUCTURING**	AI can be used in the assessment for brainstorming, creating structures, and generating ideas for improving work. **No AI content is allowed in the final submission.**
3	**AI-ASSISTED EDITING**	AI can be used to make improvements to the clarity or quality of student created work to improve the final output, but no new content can be created using AI. **AI can be used, but your original work with no AI content must be provided in an appendix.**
4	**AI TASK COMPLETION, HUMAN EVALUATION**	AI is used to complete certain elements of the task, with students providing discussion or commentary on the AI-generated content. This level requires critical engagement with AI generated content and evaluating its output. **You will use AI to complete specified tasks in your assessment. Any AI created content must be cited.**
5	**FULL AI**	AI should be used as a “co-pilot” in order to meet the requirements of the assessment, allowing for a collaborative approach with AI and enhancing creativity. **You may use AI throughout your assessment to support your own work and do not have to specify which content is AI generated.**

Table 1 The AI Assessment Scale

The student perspective on AI in education

The student’s perspective is generally considerably more positive regarding the use of AI in education than the educator’s. Studies in 2023, with data likely collected either in 2022 or in early 2023 when ChatGPT was a recent arrival, shows a positive attitude (Chan & Hu, 2023; Idroes et al., 2023) with this tool being singled out as being highly useful in academic tasks in later investigations (Mohammed Almousa & Odeh AbuSa’aleek, 2025; Slimi et al., 2025). Slimi et al., (2025) even claims it can enhance critical thinking, contradicting the principal constraint articulated by educators. Its assistance regarding writing is prevalent in the literature (Kim et al., 2025; Sumakul et al., 2022) particularly for those who need to write in academic English and for whom this is not their first language. Recent research in Ireland (O’Donnell et al., 2025) has examined the perceived benefits obtained by students using AI in assessments including study efficiency and the potential to level the playing field for students with diverse needs, echoing UNESCO’s perspective. The students interviewed called for consistency in institutional guidance on AI use in assessments showing a disparity among faculty’s expectations, perhaps linked to their knowledge and ease of use of these tools as demonstrated in Perkins et al. (2024)’s model above.

Students’ assessment of their own learning

Obtaining students’ reflections on their learning is not a novel phenomenon. Biggs mentioned it more than a quarter of a century ago in his seminal work on “quality learning” (Biggs, 1999) and various scales have since been created to capture students’ perception of their learning. Seymour et al. (2000) addressed how students could assess how different aspects of a course (e.g., assignments, teaching methods) contributed to their learning while, at the same time, reflection and metacognition were being explored as potential influencers of students’ perceived learning (Kember et al., 2000). At the time of writing, no research could be identified which explored students’ self-reported perception of their learning through an assessment at the higher end of Perkins et al’s (2024) model. Using existing research (Miao et al., 2021; Pintrich, 2002; Seymour et al., 2000; Zawacki-Richter et al., 2019), a new tool using was created for this research taking the following five elements as constructs worth exploring regarding learning potential from assessments where AI is incorporated from the outset: 1) cognitive understanding, 2) technical proficiency, 3) critical evaluation, 4) awareness of ethics and 5) metacognitive reflection.

Area for enquiry

J. Wang and Fan (2025) detail how students perceive that ChatGPT has a large positive impact on improving learning performance and has a moderately positive impact on enhancing learning perception. In slightly earlier work (Bation & Pudan, 2024), it was found that there was a significant relationship between students' attitudes toward AI and their learning outcomes. Their work underscores the importance of considering these attitudes in understanding and predicting educational outcomes. Based on this work, the following hypothesis was tested in this initial part of the study:

H1: Students' perceptions of AI in education - across affective, behavioural, and cognitive facets - will positively predict their overall perceived learning in an AI-supported assessment.

Assessment description

One core course in the undergraduate semester six curriculum at the institution in question is *Methods of Research Inquiry*, whose first learning outcome is: "Produce an up-to-date, cohesive and relevant review of academic literature on a subject of the student's choice." This outcome is assessed through a literature review assignment. In recent semesters, faculty observed increased use of generative AI in submissions. In response, a new assignment was developed, aligned with Level 4 of Perkins et al.'s (2024) model, which calls for shifting the discourse on generative AI from concerns about academic misconduct to its potential to enhance teaching and learning. The revised assignment consisted of several components as outlined Table 1 below.

Table 1 Assessment outline

<table>
<tr><th>Part</th><th>Task</th><th>Weighting</th><th>Average grade</th></tr>
<tr><td>1</td><td>Using Generative AI to write a literature review paragraph</td><td>15%</td><td>70%</td></tr>
<tr><td>2</td><td>Writing and referencing a literature review paragraph without recourse to Generative AI</td><td>30%</td><td>69%</td></tr>
<tr><td>3.1</td><td>Using Generative AI to produce a complete literature review with a gap (not assessed directly)</td><td></td><td></td></tr>
<tr><td>3.2</td><td>Analysing that gap critically</td><td>40%</td><td rowspan="2">67%</td></tr>
<tr><td>4</td><td>Reflecting on the use of Generative AI in writing a literature review</td><td>15%</td></tr>
<tr><td></td><td>Overall average</td><td></td><td>68%</td></tr>
</table>

The cohort consisted of 107 students of whom 106 completed at least one of the tasks which were spread over a period of three weeks.

Research design and methods part 1

A cross-sectional quantitative analysis was conducted using survey data collected via Microsoft Forms during one week in May 2025. The sample totalled 82 students from a population of 107 enrolled in *Methods of Research Inquiry* across four fifth-semester classes at a private Swiss international university of applied science, taught by the author. A minimum of 80 participants was required to ensure a 95% confidence level, which was achieved. To enable cross tabulating with students' grades responses were linked to participants' identities. Informed consent was therefore essential. Ethical clearance was obtained in advance, and the questionnaire was reviewed by an experienced quantitative researcher, who suggested minor edits to ensure active consent. The study's purpose and ethical considerations were explained verbally before students accessed the survey via a link or QR code. After agreeing to participate, students completed a questionnaire with three sections.

The first captured demographics (age, nationality, gender). The second used the ATTARI-WHE scale (Gnambs et al., 2025), to explore perception of AI. Due to its brevity, this scale is well suited to web-based surveys. While nine items spanned three domains: work, healthcare, and education and each was assessed through cognitive, affective, and behavioural facets, using a five-point Likert scale, only the results for the education domain are presented here. The education-related questions read: AI is helpful for learning and teaching, I have positive feelings when I think about how AI is used in education and training and If I wanted to learn something new, I would choose a learning programme with AI rather than one without. The three facets together showed low reliability ($\alpha = .55$); therefore, analyses treated them separately. The third section assessed students' perceived learning from the assignment requiring critical engagement with generative AI. Although the CAP scale (Rovai et al., 2009) was initially considered, it was not well aligned with the learning dimensions outlined in Perkins et al.'s (2024) model. Instead, a novel five-dimensional scale exploring cognitive understanding, technical proficiency, critical evaluation, ethical awareness, and metacognitive reflection was created, as mentioned above, underpinned by Seymour et al.'s (2000) work on self-assessed learning gains (SALG). All statements used a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The full list of dimensions and statements appears in Table 2.

Table 2 Five-dimensional scale rating perception of self-reported learning from an assessment using generative AI

Dimension	Statement
Cognitive understanding (CU 1-3)	The assessment helped me understand how to use Generative AI tools to support academic writing tasks.
	The assessment helped me distinguish between appropriate and inappropriate uses of Generative AI in an academic setting.
	The assessment helped me know how to fact-check and verify AI-generated content.
Technical proficiency (TP 1-2)	The assessment helped me learn how to effectively prompt an AI tool to generate useful content.
	The assessment helped me learn how to refine AI-generated outputs to meet academic standards.
Critical evaluation (CE 1-2)	The assessment helped me learn how to critically assess the reliability and limitations of AI-generated information.
	The assessment helped me learn how AI tools may introduce errors in academic work.
Ethical awareness (EA 1)	The assessment helped me understand the ethical considerations when using AI for assessments.
Metacognitive reflection (MR 1)	As a result of the assessment, I have decided to change the way I use AI for academic work.

Perceived learning outcomes were analysed for internal consistency in the three multi-item domains: cognitive understanding ($\alpha = .86$), technical proficiency ($\alpha = .67$), and critical evaluation ($\alpha = .75$). The overall perceived-learning index demonstrated high reliability ($\alpha = .92$).

The questionnaire ended with one final, non-obligatory, open-ended question: “Any other comments on your perception of AI as a result of your first MoRI [Methods of Research Inquiry] assignment?”. Data were analysed by the author using SPSS.

Results

Descriptive demographic statistics

The mean age of the participants was 21 with 29 claimed nationalities. Of the 82 participants in the sample, one preferred not to reveal a gender, 28 responded “man” and 53 responded “woman”.

Descriptive statistics

As presented in Table 3 below, perceived learning outcomes were generally high (Ms = 3.45–4.32). The strongest ratings were for critical evaluation skills, including identifying AI errors (CE2; M = 4.32, SD = 0.84) and distinguishing appropriate use (CU2; M = 4.17, SD = 0.89). Lower scores were observed for behavioural intentions (EDU BEH; M = 3.45, SD = 1.07) and metacognitive reflection (MR1; M = 3.68, SD = 1.15).

Table 3 Descriptive statistics

	EDU AFF	EDU BEH	EDU COG	CU 1	CU 2	CU 3	TP 1	TP 2	CE 1	CE 2	EA 1	MR 1
count	82	82	82	82	82	82	82	82	82	82	82	82
mean	3.866	3.451	4.11	3.829	4.171	4.146	3.817	3.683	4.146	4.317	3.89	3.683
std	0.886	1.068	0.685	1.04	0.886	0.957	0.931	1.029	0.833	0.844	0.93	1.153

Inferential statistics

Regression analyses support the hypothesis indicating that students' perceptions of AI in education significantly predicted their overall perceived learning, explaining 18% of the variance, $R^2 = .18$, $F(3, 78) = 5.52$, $p = .002$. Within this model, the affective facet emerged as the only significant predictor ($\beta = 0.25$, SE $= 0.10$, $p = .014$), suggesting that students who reported more positive feelings toward AI also reported higher levels of perceived learning. In contrast, behavioural and cognitive perceptions were not significant predictors (ps $\geq .22$).

When the five learning subdomains were examined separately, model fit was significant for cognitive understanding ($R^2 = .19$, $p < .001$) and critical evaluation ($R^2 = .19$, $p < .001$), marginal for technical proficiency ($R^2 = .09$, $p = .064$), and non-significant for ethical awareness and metacognitive reflection. Across all significant models, the affective facet consistently predicted perceived learning outcomes: cognitive understanding ($\beta = 0.27$, $p = .018$), critical evaluation ($\beta = 0.24$, $p = .018$), and technical proficiency ($\beta = 0.30$, $p = .014$). Behavioural and cognitive facets were not significant in any model.

Together, these results suggest that students' emotional orientation toward AI rather than their behavioural intentions or cognitive evaluations plays the most powerful role in shaping how much they believe they have learned from the AI-supported assessment.

The qualitative comments were compared to the exam results showing that those who received the highest grades valued the assessment's requirement of critical thinking and acknowledged the limitations of using AI. The students who achieved a failing grade for the assignment produced more diverse responses including a lack of comprehension of the purpose of the assessment. It is to be noted that, despite the instructions for part 3.2 specifically requiring the students' own thoughts, many turned to generative AI to create the text submitted. When this was clearly identified by the faculty, the work received a failing grade.

Discussion and recommendations

Turning first to the descriptive statistics, it is evident that this novel assessment, despite the moderate grade average, was perceived by the students as being effective predominantly in the areas of critical evaluation and cognitive understanding. As AI can now perform the highest of Bloom's learning levels, "create", it is beholden on teachers to formulate assignments which engage the critical thinking of the students on the work which either AI creates or they co-create with AI as expounded in the highest level of Perkins et al.'s (2024) model.

Analysis of the inferential statistics demonstrates that how students feel about AI matters more than what they think or plan to do in their perception of learning through this assessment. As such, educators need to craft activities that foster positive feelings toward AI (e.g., icebreaker tasks, low-stakes exploration, collaborative challenges) to encourage engagement and reduce apprehension. Psychologically safe teaching environments should foster an approach that views critical use of AI as enabling growth – while at the same time providing clear and consistent guidance as to what is considered as cheating. Students should be constantly encouraged to analyse the outputs of AI in terms of accuracy, bias and relevance, understanding its limits and its capacity to render them expert users of these tools. They will then be well equipped for the professional environment where their ability to work efficiently and effectively with these tools will be valued.

Limitations and suggestions for further research

The use of self-reported data regarding student learning could lead to bias and, while the confidence level is high from the study's population, the ability to generalise to a wider population is limited due to the small-scale nature of the study. With its quantitative design, this study was not able to capture the richness of students' attitudes towards AI in the assessment. Such data were gathered however in the second part of this mixed-methods study which gathered interview data from the same cohort to explore their perception of AI's usefulness, limitations, trustworthiness and ethics. The results of this study will be published later. Further academic work could be undertaken with a larger sample size to address the issue of generalisability.

References

Abuzar, M., Mahmudulhassan, & Muthoifin. (2025). University students' trust in AI: Examining reliance and strategies for critical engagement. *International Journal of Interactive Mobile Technologies*, *19*(7), 70–82. https://doi.org/10.3991/ijim.v19i07.52875

Barrett, A., & Pack, A. (2023). Not quite eye to A.I.: Student and teacher perspectives on the use of generative artificial intelligence in the writing process. *International Journal of Educational Technology in Higher Education*, *20*(1), 59. https://doi.org/10.1186/s41239-023-00427-0

Bation, N. D., & Pudan, J. C. (2024). Exploring the correlation between students' attitudes towards AI and their learning outcomes. *International Journal of Social Science and Human Research*, *07*(02), 1243–1247. https://doi.org/10.47191/ijsshr/v7-i02-45

Biggs, J., B. (1999). *Teaching for quality learning at university: What the student does* (1st ed.). Taylor & Francis.

Caucheteux, C., Hodgkins, L.-B., Batifol, V., Fouché, L., & Romero, M. (2024). Students' perspective on the use of artificial intelligence in education. In A. Urmeneta & M. Romero (Eds.), *Creative applications of artificial intelligence in education*. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-55272-4

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), 43. https://doi.org/10.1186/s41239-023-00411-8

Delcker, J., Heil, J., Ifenthaler, D., Seufert, S., & Spirgi, L. (2024). First-year students AI-competence as a predictor for intended and de facto use of AI-tools for supporting learning processes in higher education. *International Journal of Educational Technology in Higher Education*, *21*, 1–13. https://doi.org/10.1186/s41239-024-00452-7

Gnambs, T., Stein, J.-P., Appel, M., Griese, F., & Zinn, S. (2025). An economical measure of attitudes towards artificial intelligence in work, healthcare, and education (ATTARI-WHE). *Computers in Human Behavior: Artificial Humans*, *3*, 100106. https://doi.org/10.1016/j.chbah.2024.100106

Guadamuz, A. (2025, April 14). How many people are using generative AI on a daily basis? A Gemini report. *TechnoLlama*. https://www.technollama.co.uk/a-gemini-report-how-many-people-are-using-generative-ai-on-a-daily-basis-a-gemini-report

Hamilton, I. (2024, 6). *Artificial intelligence in education: Teachers' opinions on AI in the classroom*. Forbes Advisor. https://www.forbes.com/advisor/education/it-and-tech/artificial-intelligence-in-school/

Idroes, G. M., Noviandy, T. R., Maulana, A., Irvanizam, I., Jalil, Z., Lensoni, L., Lala, A., Abas, A. H., Tallei, T. E., & Idroes, R. (2023). Student perspectives on the role of artificial intelligence in education: A survey-based analysis. *Journal of Educational Management and Learning*, *1*(1), 8–15. https://doi.org/10.60084/jeml.v1i1.58

Ivanov, S. (2023). The dark side of artificial intelligence in higher education. *Service Industries Journal*, *43*(15/16), 1055–1082. https://doi.org/10.1080/02642069.2023.2258799

Johnston, H., Wells, R. F., Shanks, E. M., Boey, T., & Parsons, B. N. (2024). Student perspectives on the use of generative artificial intelligence technologies in higher education. *International Journal for Educational Integrity*, *20*(1), 2. https://doi.org/10.1007/s40979-024-00149-4

Kember, D., Leung, D. Y. P., Jones, A., Loke, A. Y., McKay, J., Sinclair, K., Tse, H., Webb, C., Yuet Wong, F. K., Wong, M., & Yeung, E. (2000). Development of a questionnaire to measure the level of reflective thinking. *Assessment & Evaluation in Higher Education*, *25*(4), 381–395. https://doi.org/10.1080/713611442

Kim, J., Yu, S., Detrick, R., & Li, N. (2025). Exploring students' perspectives on Generative AI-assisted academic writing. *Education and Information Technologies*, *30*(1), 1265–1300. https://doi.org/10.1007/s10639-024-12878-7

Kosmyna, N., Hauptmann, E., Yuan, Y. T., Situ, J., Liao, X.-H., Beresnitzky, A. V., Braunstein, I., & Maes, P. (2025). *Your brain on ChatGPT: Accumulation of cognitive debt when using an AI assistant for essay writing task* (No. arXiv:2506.08872; Version 1). arXiv. https://doi.org/10.48550/arXiv.2506.08872

McKinsey & Company. (2025). *AI in the workplace: A report for 2025*. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/superagency-in-the-workplace-empowering-people-to-unlock-ais-full-potential-at-work

Miao, F., Holmes, W., Ronghuai, H., & Hui, Z. (2021). *AI and education: Guidance for policy-makers*. UNESCO. https://doi.org/10.54675/PCSP7350

Mogavi, R. H., Deng, C., Juho Kim, J., Zhou, P., Kwon, Y. D., Metwally, A. H. S. M., Tlili, A., Bassanelli, S., Bucchiarone, A., Gujar, S., Nacke, L. E., & Hui, P. (2024). ChatGPT in education: A blessing or a curse? A qualitative study exploring early adopters' utilization and perceptions. *Computers in Human Behavior: Artificial Humans*, *2*(1), 100027. https://doi.org/10.1016/j.chbah.2023.100027

Mohammed Almousa, M., & Odeh AbuSa'aleek, A. (2025). Postgraduate students' attitude toward using ChatGPT in enhancing their master's thesis: A mixed method study. *Arab World English Journal*, *1*, 157–175. https://doi.org/10.24093/awej/AI.9

O'Donnell, F. O., Porter, M., & Fitzgerald, S. (2025). The role of artificial intelligence in higher education: Higher education students use of AI in academic assignments. *Irish Journal of Technology Enhanced Learning*, *8*(1). https://doi.org/doi.org/10.22554/szwjfy54

Perkins, M., Furze, L., Roe, J., & MacVaugh, J. (2024). The AI assessment scale (AIAS): A framework for ethical integration of generative AI in educational assessment. *Journal of University Teaching and Learning Practice*, *21*(06). https://doi.org/10.53761/q3azde36

Perlin, J. (2023). *A Forest Journey: The Role of Trees in the Fate of Civilization*. Patagonia. https://www.patagonia.com/product/a-forest-journey-the-role-of-trees-in-the-fate-of-civilization/BK895.html

Pintrich, P. R. (2002). The role of metacognitive knowledge in learning, teaching, and assessing. *Theory Into Practice*, *41*(4), 219–225. https://doi.org/10.1207/s15430421tip4104_3

Putri, D., & Sain, Z. (2025). From chalkboards to chatbots: Revolutionizing education with AI-driven learning innovations. *Educative: Jurnal Ilmiah Pendidikan*, *3*, 1–10. https://doi.org/10.70437/educative.v3i1.823

Rovai, A. P., Wighting, M. J., Baker, J. D., & Grooms, L. D. (2009). Development of an instrument to measure perceived cognitive, affective, and psychomotor learning in traditional and virtual classroom higher education settings. *The Internet and Higher Education*, *12*(1), 7–13. https://doi.org/10.1016/j.iheduc.2008.10.002

Seymour, E., Wiese, D., Hunter, A.-B., & Daffinrud, S. (2000, March 27). *Creating a better mousetrap: On-line student assessment of their learning gains*. National Meetings of the American Chemical Society Symposium, San Francisco.

Silva, S., Silva, C., & Oliveira, M. (2025). The value of skills for a sustainable tourism and hospitality industry. *Tourism and Hospitality*, *6*(1), 14. https://doi.org/10.3390/tourhosp6010014

Singer-Freeman, K., Verbeke, K., & Barre, B. (2025). Generative AI usage among university students depends on academic level and task. *Higher Learning Research Communications*, *15*(2), 1–25. https://doi.org/10.18870/hlrc.v15i2.1616

Slimi, Z., Benayoune, A., & Alemu, A. E. (2025). Students' perceptions of artificial intelligence integration in higher education. *European Journal of Educational Research*, *14*(2), 471–484. https://doi.org/10.12973/eu-jer.14.2.471

Sumakul, D. T. Y. G., Hamied, F. A., & Sukyadi, D. (2022). Students' perceptions of the use of AI in a writing class. *67th TEFLIN International Virtual Conference & the 9th ICOELT 2021 (TEFLIN ICOELT 2021)*, 52–57. https://doi.org/10.2991/assehr.k.220201.009

Wang, J., & Fan, W. (2025). The effect of ChatGPT on students' learning performance, learning perception, and higher-order thinking: Insights from a meta-analysis. *Humanities and Social Sciences Communications*, *12*(1), 621. https://doi.org/10.1057/s41599-025-04787-y

Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the potential impact of artificial intelligence (AI) on international students in higher education: Generative AI, chatbots, analytics, and international student success. *Applied Sciences*, *13*(11), Article 11. https://doi.org/10.3390/app13116716

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