Towards Pedagogically Structured Human–AI Engagement in a Peer Learning Context

DOI
https://doi.org/10.18690/um.fov.4.2026.34

ISBN
978-961-299-152-4

Minna Silvennoinen, Sanna Paananen, Sami Määttä, Satu Aksovaara

Jamk University of Applied Sciences Jyväskylä, School of Professional Teacher Education, Jyväskylä, Finland
minna.silvennoinen@jamk.fi, sanna.paananen@jamk.fi, sami.maatta@gmail.com, satu.aksovaara@jamk.fi

Generative AI is increasingly integrated into higher education, yet prior research has mainly examined AI use at the individual level, with less attention on AI engagement variation across learning tasks, AI roles, and collaborative contexts. This study examined perceived AI usability across a pedagogically structured peer-learning process where generative AI supported different, individual or collaborative learning activities. The context was a compulsory undergraduate course where student teams worked on authentic projects. Responses from 411 students indicate that generative AI was perceived as most usable during collaborative content structuring and least usable during individual reflection. Students' perceived study ability showed small but consistent associations with perceived AI usability. Similar patterns emerged within teams, suggesting that ways of engaging with generative AI may partly develop as shared practices with study-related self-regulation potentially playing a role. Findings highlight the importance of examining AI engagement as a phenomenon shaped by pedagogical task design, collaborative learning, and the roles assigned to generative AI in learning activities.

Keywords:
generative AI,
human–AI collaboration,
peer learning,
higher education,
pedagogical design

University of Maribor Press

1 Introduction

As generative AI (GenAI) becomes an increasingly embedded element of everyday academic practices in higher education (HE) (Carmi, 2025), attention is focusing on how such use becomes pedagogically meaningful. Students differ in how they engage with new technologies (Zou Y. et al., 2025), and GenAI use is known to range from shallow copy-and-paste practices to more reflective interaction (Chen et al., 2026), Yet, little is known about how such use varies across task types, AI roles, and social contexts (Belkina et al., 2025; Qian, 2025). This raise questions about how structured tasks could support intentional human–AI collaboration, highlighting the need for more structured pedagogical approaches that support deeper and more reflective engagement with GenAI in higher-order learning processes (Qian, 2025).

Previous research has largely examined students' use of GenAI at the individual level (Ruiz-Rojas et al., 2024; Salinas-Navarro et al., 2024). However, in collaborative learning contexts, AI engagement may also be shaped by team characteristics and interaction practices. Emerging studies suggest that the roles GenAI takes in collaborative activities can vary depending on team dynamics and users' technological expertise (e.g., Law et al., 2025; Anderson et al., 2025). Nevertheless, relatively little research has examined how pedagogically structured AI roles within learning tasks relate to shared patterns of AI engagement.

Understanding task-specific patterns of human–AI collaboration requires attention to learner-related psychological factors, such as perceived study ability, which may influence how students integrate GenAI into their learning activities (Atchley et al., 2024). Examining these factors may explain why some students engage more actively with GenAI while others make more limited use of it, particularly in tasks requiring analytical framing or reflection.

Universities of applied sciences (UAS) face a growing need to prepare students for AI engagement in professional practice. This human–AI collaboration — the ability to work effectively in teams composed of both humans and AI systems (Atchley et al., 2024) becomes increasingly important for future employability (e.g., Irish et al., 2025; Portocarrero Ramos et al., 2025). Recent research has highlighted the importance of integrating GenAI into collaborative, project-based learning environments that support knowledge co-creation and student agency in orchestrating interactions between humans and AI (e.g., Law et al. 2025). This raises questions relating to pedagogical structuring of human-AI collaboration within HE (McPhee & Jerowsky, 2025) and further highlights the importance of examining AI engagement as a phenomenon shaped by pedagogical design, social contexts, and learner-related characteristics.

This study investigates how students report GenAI usability across phases of a pedagogically structured peer-learning process in which GenAI takes different supportive or facilitative roles. Research questions are:

RQ1: How do students' perceived AI usability differ across individual and collaborative learning tasks where GenAI serves different roles?

RQ2: How is students' study ability associated with their perceived AI usability across varying GenAI roles?

RQ3: To what extent does students' perceived AI usability with varying GenAI roles show similarities within project teams?

This study contributes to the emerging literature on AI in HE by moving beyond individual use to examine perceived AI usability and patterns of AI use within peer-learning contexts across task types and pedagogically structured uses of GenAI. The findings provide empirical insight into how task design and social context may shape AI use, contributing to understanding how pedagogical structuring can support meaningful human–AI collaboration in HE.

2 Background

Previous research has shown that students commonly employ GenAI for idea generation, text production, revision, and conceptual clarification (Krause et al., 2024; Qian, 2025). Yet, although adoption is widespread, research indicates that engagement often remains uneven and tied to isolated uses of GenAI, as well as being characterised by individual trial and error (Almassaad et al., 2024; Belkina et al., 2025; Krause et al., 2024; Huang et al., 2024). Although recent studies have explored the use of GenAI in tasks requiring higher-order cognitive processes, such as problem-solving, and reflection, findings remain mixed and highly dependent on pedagogical design and task structure, particularly in terms of guided versus unguided use (Guo et al. 2025; Balart et al. 2025). At the same time, students report uncertainty regarding appropriate and responsible uses of GenAI within learning, pointing to continuing inconsistencies in institutional guidance and a lack of pedagogically structured support (e.g. Abdelaal et al., 2025; Balabdaoui et al., 2024).

In response, pedagogical frameworks for AI integration have been proposed. AI literacy models often conceptualize AI-related competences through hierarchical learning frameworks, such as Bloom's taxonomy (e.g., Zhou & Schofield, 2024) or extend existing digital competence traditions, such as TPACK or DigCompEdu, to the context of GenAI (e.g., Zou D. et al., 2025). However, much of this work focuses on defining competencies or guiding teachers' integration of AI.

Although human–AI collaboration involving GenAI has received increasing attention in recent research (e.g., Jung & Jin, 2025; Jia et al. 2026), less is known about how GenAI use unfolds within pedagogically structured peer-learning contexts. Research conceptualizes peer learning as a socially shared process in which knowledge is co-constructed through interaction, negotiation, and shared regulation among learners (Järvelä et al., 2023). GenAI use in learning may support collaborative processes, while its role and use within these contexts may also be shaped by group-level dynamics and shared practices, since the use is not solely an individual decision (e.g. Sichterman et al., 2025; Pham et al., 2025; Feng, 2025). These team-level dynamics may lead to shared patterns of AI engagement and mirror emerging forms of human–AI collaboration within teamwork. Peer-learning contexts provide a natural setting for introducing new technologies into collaborative work, where students can explore and negotiate GenAI use while working toward shared outcomes.

While pedagogical structuring shapes how GenAI is embedded within learning tasks, students' engagement with these structures may also depend on individual learner-related psychological factors. These factors may play an important role in shaping how students engage with GenAI in academic contexts. Students differ in their psychological readiness to adopt and integrate new technologies, which make perceived study ability particularly relevant for understanding patterns of GenAI use (Acosta-Enriquez et al., 2024; Hadar Shoval, 2025). Perceived study ability can be understood in relation to self-regulated learning, which involves planning, monitoring, and managing one's learning (Zimmerman, 2002; Schraw & Dennison, 1994). Students with stronger self-regulatory capacities may be better able to integrate GenAI into their learning, whereas lower perceived study ability may be associated with more limited use. In peer learning contexts, these individual characteristics may also interact with team-level dynamics, potentially contributing to shared patterns of GenAI use.

3 Research Design and Methodology

3.1 Context, Participants and Research Design

This study examined students' perceived AI usability in a course integrating GenAI. The study was guided by the **AI Assistant Framework**, in which GenAI use was pedagogically orchestrated through learning task instructions positioning GenAI in roles presented in Table 1. The approach draws on principles of design-based research, where pedagogical interventions are embedded in authentic learning contexts and examined in practice (Wang & Hannafin, 2005).

The study was conducted in a compulsory 10 ECTS undergraduate course organised around peer-learning principles, where students worked in multidisciplinary teams on authentic working-life projects. The course was implemented in two consecutive years (2024–2025) using the same pedagogical design, and the data from both cohorts were combined for analysis.

A total of 544 students (79.6%) consented to participate in the study, of whom 411 answered all perceived AI usability items. Of the participants, 49.8% were male and 46.5% female (3.7% missing). Students represented degree programmes in business, health and wellbeing, and technology. They worked in teams of four to five members (M = 4.64), forming 149 project teams.

GenAI was integrated into five phases of the learning process (P1-P5), with task instructions guiding how students engaged with GenAI in each project phase. The tasks differed in both their social configuration (individual vs. team) and their functional role in the learning process, see Table 1.

Table 1: Pedagogically structured AI-supported tasks across project phases

Learning phase	Learning task	GenAI role	Mode
P1 Ideation	Client meeting	Ideation support	Individual
P2 Analysis	Competence identification	Skill analysis support	Team
P3 Problem solving	Teamwork challenges and process reflection	Teamwork coaching	Team
P4 Production	Project presentation	Content structuring	Team
P5 Reflection	Reflection	Reflection support	Individual

The design enabled comparison of perceived AI usability across phases, analysis of its association with study ability and team-level similarity, and comparisons within students across tasks.

3.2 Measures

Perceived AI usability was measured across the five phases of the AI Assistant Framework (P1–P5) using two self-report items per phase on a five-point Likert scale. The items assessed perceived AI competence ("I was able to use AI in finding a solution/ completing the task") and perceived ease of use ("Using AI in the task was easy"). For each phase, a composite perceived AI usability score was calculated as the mean of the two items. Internal consistency for the two-item scales was acceptable across phases (Table 2).

Study ability was measured using a scale derived from the HowULearn instrument (Parpala & Lindblom-Ylänne, 2012), based on the Metacognitive Awareness Inventory (Schraw & Dennison, 1994). The scale includes two dimensions—knowledge about cognition and regulation of cognition—measured on a five-point Likert scale. Cronbach's α for the scale was .88.

3.3 Analytical Strategy

Patterns of **perceived AI usability** across the five phases (P1–P5) were examined using descriptive statistics, and phase differences were tested with a repeated-measures ANOVA. To examine associations between students' **study ability** and perceived AI usability, Pearson correlations (two-tailed) were calculated between the study ability scale and each of the five perceived AI usability scores P1–P5. Pairwise deletion was used to maximize the number of available cases.

To assess **team-level similarity** in perceived AI usability (RQ3), **intraclass correlation coefficients** (ICC) were calculated for each phase using a one-way random-effects model with team as the grouping factor. Variance components were obtained using UNIANOVA in SPSS. The actual average team size (k = 4.64) was applied in the ICC formulas. ICC(1) represents the proportion of variance attributable to team membership, whereas ICC(2) indicates the reliability of aggregated team-level means. All analyses were conducted using IBM SPSS Statistics 31, with statistical significance evaluated at $p < .05$. ICC values between .05 and .20 were interpreted as indicating small to moderate clustering.

4 Results

RQ1. Differences in perceived AI usability across learning tasks

Perceived AI usability across the P1–P5 was examined. Descriptive statistics (*M* and *SD*), reliability estimates, and intercorrelations among the task-specific perceived AI usability scores are presented in Table 2.

Table 2: Descriptive statistics and intercorrelations for perceived AI usability

Phase	α	*M*	*SD*	P1	P2	P3	P4	P5
P1 Ideation (Individual) **Ideation support**	0.87	2.68	1.14	—				
P2 Analysis (Team) **Facilitating skill analysis**	0.89	2.86	1.16	0.65	—			
P3 Problem solving (Team) **Teamwork coaching**	0.88	2.77	1.16	0.64	0.80	—		
P4 Production (Team) **Content structuring**	0.88	3.04	1.18	0.49	0.51	0.55	—	
P5 Reflection (Individual) **Reflection support**	0.86	2.49	1.13	0.72	0.67	0.72	0.60	—

Note. M = mean; SD = standard deviation. Cronbach's α is reported for each two-item scale.
All correlations are Pearson's r (two-tailed), p < .001.

Internal consistency for the two-item scales was acceptable across tasks (Cronbach's α = .86–.89). Intercorrelations among the perceived AI usability scores were positive and statistically significant (all $p < .001$), ranging from $r = .49$ between P1 and P4 to $r = .80$ between P2 and P3. Results of the repeated-measures ANOVA and Bonferroni-adjusted pairwise comparisons are presented in Table 3.

Table 3: Repeated-measures ANOVA and pairwise comparisons for perceived AI usability

A. Omnibus ANOVA (Greenhouse–Geisser corrected)

Source	df1	df2	F	p	Partial η^2
Learning task	3.387	1388.621	35.717	< .001	.080

Note. Greenhouse–Geisser correction was applied due to violation of sphericity (Mauchly's $W = .684$, $p < .001$).

B. Pairwise comparisons (Bonferroni-adjusted)

Comparison	Mean difference	SE	p	95% CI Lower	95% CI Upper
P1 vs P2	-0.180	0.047	.002	-.313	-.047
P1 vs P3	-0.094	0.048	.537	-.230	.043
P1 vs P4	-0.359	0.058	< .001	-.521	-.196
P1 vs P5	0.193	0.042	< .001	.076	.311
P2 vs P3	0.086	0.036	.180	-.016	.189
P2 vs P4	-0.179	0.057	.019	-.340	-.018
P2 vs P5	0.373	0.046	< .001	.244	.503
P3 vs P4	-0.265	0.055	< .001	-.420	-.111
P3 vs P5	0.287	0.042	< .001	.168	.406
P4 vs P5	0.552	0.051	< .001	.409	.696

Note. SE = standard error; P1 = Ideation; P2 = Analysis; P3 = Problem solving; P4 = Production; P5 = Reflection. All p-values are Bonferroni-adjusted.

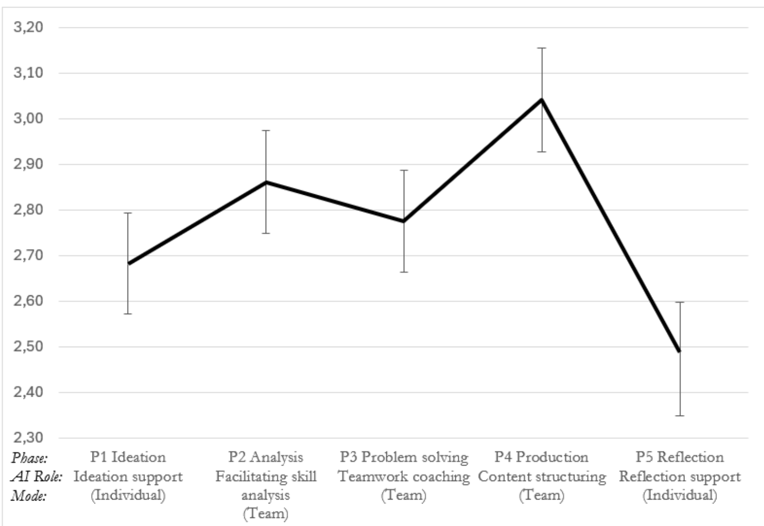

Figure 1: Mean perceived AI usability across learning tasks (P1–P5)

The repeated-measures ANOVA indicated significant differences in perceived AI usability across the P1–P5, $F(3.39, 1388.62) = 35.72$, $p < .001$, partial $\eta^2 = .08$ (see Table 3). Bonferroni-adjusted pairwise comparisons further indicated that perceived AI usability was highest in P4 Production and lowest in P5 Reflection, while P1–P3 formed a middle cluster with only one significant difference (between P1 and P2). Descriptively, perceived AI usability appeared somewhat lower in the individual tasks P1 and P5 than in the team-based tasks P2–P4. Figure 1 illustrates the mean perceived AI usability across the five tasks ($N = 411$), with error bars representing 95% confidence intervals.

RQ2. Study ability and perceived AI usability

To address RQ2, correlations between study ability and perceived AI usability across the five learning tasks were examined. The results are presented in Table 4.

Table 4: Correlations between study ability and perceived AI usability

Phase	*r*	*p*
P1 Ideation	.10	.032
P2 Analysis	.13	< .001
P3 Problem solving	.09	.029
P4 Production	.055	.236
P5 Reflection	.11	.020

Note. r = Pearson correlation coefficient.

Study ability showed generally weak associations with perceived AI usability across learning tasks (see Table 4). The strongest positive correlation was observed for P2 ($r = .13$, $p < .001$). Smaller positive correlations were found for P1 ($r = .10$, $p = .032$), P3 ($r = .09$, $p = .029$), and P5 ($r = .11$, $p = .020$). No statistically significant association was found for P4 ($r = .055$, $p = .236$).

RQ3. Team-level similarity in perceived AI usability

To address RQ3, intraclass correlation coefficients (ICC) were calculated to examine team-level similarity in perceived AI usability across the five learning tasks. The results are presented in Table 5.

Table 5. Intraclass correlation coefficients for perceived AI usability tasks

Phase	ICC(1)	ICC(2)
P1 Ideation	.10	.34
P2 Analysis	.15	.45
P3 Problem solving	.09	.32
P4 Production	.12	.38
P5 Reflection	.09	.33

Note. ICC(1) indicates the proportion of variance attributable to team membership; ICC(2) indicates the reliability of team-level means.

ICC(1) values ranged from .09 to .15, indicating small but noticeable similarity in perceived AI usability within teams across learning tasks. The highest ICC(1) value was observed for P2 (.15), followed by P4 (.12). Lower values were observed for P1 (.10), P3 (.09), and P5 (.09). ICC(2) values ranged from .32 to .45, remaining below the commonly suggested threshold for reliable aggregation of team-level means.

5 Discussion

This study provides new insight into how perceived AI usability varies across phases of the learning process, within student teams, and in relation to study ability, and illustrates how structured GenAI roles in peer-learning contexts may shape students' engagement with AI. Firstly, perceived AI usability varied across the phases of the learning process (RQ1), with the highest levels observed during collaborative production (P4) and the lowest during individual reflection (P5). This may suggest that AI is perceived as more useful in phases involving content development and the preparation of shared outputs. Similar observations have been reported in earlier studies showing that students often apply GenAI for idea generation, drafting, and content development (e.g., Krause et al., 2024; Chen et al., 2026).

Secondly the results highlight the role of **social learning context**, while perceived AI usability was higher when addressing teamwork challenges P3 than as individual reflection support P5, suggesting that collaborative contexts may provide additional opportunities for students to experiment with GenAI when engaging in tasks involving reflection. Positioning of GenAI within the social structure of the learning process may thus influence how useful students perceive AI support to be. ICC analyses indicate also small but consistent within-team similarity in perceived AI usability, strongest while GenAI was supporting skill analysis (P2) and moderately visible in content structuring (P4), both requiring shared interpretation or coordinated team outputs. In contrast, phases involving more reflection (P3 & P5), showed lower similarity within teams. The findings can be interpreted through a peer-learning perspective, suggesting that AI use is not only an individual behaviour but is shaped through shared practices and collaborative processes within student teams (see also e.g. Sichterman et al. 2025). This aligns with research on peer learning and shared regulation, where learning emerges through interaction and co-construction rather than individual action alone.

Thirdly, reflective learning places high demands on **metacognitive regulation**, while effective use of GenAI similarly requires learners to formulate goals and critically evaluate AI outputs (e.g. Wang, 2023). As Levin et al. (2025) note, these metacognitive capacities are not automatically activated, which may explain the low perceived usability of AI in P5. In line with this, study ability showed weak but consistent associations with perceived AI usability and students with higher study ability perceived AI as slightly more usable.

Taken together, these findings suggest that perceived AI usability reflects both individual metacognitive experiences and shared practices within teams, as indicated by variation across learning phases and modest within-team similarity. When learning activities require collective sensemaking or coordinated outputs, results are consistent with CSCL research on shared learning practices (Fischer et al., 2013). However, ICC varied across learning phases and team similarity appeared linked to the pedagogical role assigned to GenAI in each task, suggesting that shared human–AI collaboration practices may develop when AI engagement is embedded in structured collaborative learning activities.

This study relied on self-reported measures, which may not fully reflect actual practices, limiting the construct validity of the measures. The findings are also based on a single course context, within one institution and team interaction processes were not directly measured. This limits conclusions about the underlying mechanisms through which shared AI practices emerge.

At the same time, the study was situated in a task-based peer-learning environment that reflects common features of project-based higher education. The integration of GenAI into real-world tasks provides a context that closely resembles how AI is used in both educational and professional settings. While the findings cannot be directly generalised, they may offer indicative insights into how pedagogically structured AI use functions in similar collaborative learning environments

The findings contribute to discussions on pedagogical frameworks for AI integration by suggesting that GenAI can function as a collaborative partner whose role varies across learning phases. This aligns with broader frameworks emphasising AI-supported problem solving, collaboration, and learner agency (e.g., UNESCO, 2024), while extending them by showing how these principles become visible in practice through pedagogically structured AI roles. In contrast to frameworks that primarily emphasise AI competencies or instructional use (e.g., Zhou & Schofield; Zou D. et al., 2025), this perspective positions GenAI roles within the learning process itself. The study thus shifts attention from general AI competencies toward the design of learning processes in which meaningful and context-sensitive AI use can emerge.

Conclusions

This study advances understanding of how pedagogical design can support meaningful human–AI collaboration in HE. It shows how structured tasks and peer-learning contexts can make human–AI collaboration more visible, purposeful, and accessible to students with different levels of metacognition. The pedagogical focus should therefore be on instructional guidance that supports meaningful use of GenAI, particularly in reflective and metacognitively demanding tasks, rather than assuming such engagement emerges spontaneously.

Future research should move beyond viewing human–AI collaboration as an individual skill and examine how pedagogical design, learners' self-regulatory capacities, and collaborative contexts shape human–AI practices, framing AI use as a socio-technical learning process shaped by tasks and team dynamics.

End notes

Use of Generative AI in the Writing Process. Generative AI tools were used to support language editing and to assist in identifying potentially relevant literature during the literature search. All sources were independently verified by the authors, who take full responsibility for the manuscript.

References

Abdelaal, M. S., AbdElaal, E.-S., Janssen, A., Smith, E., & Diaby, A. L. (2025). Integrating GenAI in higher education: The critical voices shaping pedagogy and integrity. In S. Barker, S. Kelly, R. McInnes, & S. Dinmore (Eds.), *Futurefocused: Educating in an era of continuous change. Proceedings ASCILITE 2025* (pp. 188–198). https://doi.org/10.65106/apubs.2025.2639

Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Arbulu Perez Vargas, C. G., Huamaní Jordan, O., & López Roca, C. (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: Effect of intent to use, verification of information and responsible use. *BMC Psychology*, 12(1), 255. https://doi.org/10.1016/j.heliyon.2024.e38315

Almassaad, A., Alajlan, H., & Alebaikan, R. (2024). Student Perceptions of Generative Artificial Intelligence: Investigating Utilization, Benefits, and Challenges in Higher Education. *Systems*, *12*(10), 385. https://doi.org/10.3390/systems12100385

Anderson, E., Lin, G. C., Farid, A., Fenech, M., Hanks, B., Klopfer, E., ... & Nguyen, A. (2025). Exploring Genai Technologies within collaborative learning. In Proceedings of the 18th International Conference on Computer-Supported Collaborative Learning-CSCL 2025, pp. 499-506. International Society of the Learning Sciences.

Atchley, P., Pannek, H., Wofford, K., Hopkins, M., & Atchley, R. A. (2024). Human and AI collaboration in the higher education environment: Opportunities and concerns. *Cognitive Research: Principles and Implications, 9*(20). https://doi.org/10.1186/s41235-024-00547-9

A Systematic Literature Review on the Pedagogical Implications and Impact of GenAI on Students' Critical Thinking https://doi.org/10.3390/a19030179

Balabdaoui, F., Dittmann-Domenichini, N., Grosse, H., et al. (2024). A survey on students' use of AI at a technical university. *Discover Education*, 3, 51. https://doi.org/10.1007/s44217-024-00136-4

Belkina, M., Daniel, S., Nikolic, S., Haque, R., Lyden, S., Neal, P., Grundy, S., & Hassan, G. M. (2025). *Implementing generative AI (GenAI) in higher education: A systematic review of case studies.* Computers and Education: Artificial Intelligence, 8, 100407. https://doi.org/10.1016/j.caeai.2025.100407

Carmi, G. (2025). Learning with Generative AI: An Empirical Study of Students in Higher Education. Education Sciences, 15(12), 1696. https://doi.org/10.3390/educsci15121696

Chen, Y., Shi, X., Liu, X., Wang, S., Liu, T. X., & Gašević, D. (2026). Not all students engage alike: Multi-institution patterns in GenAI tutor use. *arXiv*. https://arxiv.org/abs/2602.00447

Dillenbourg, P., & Jermann, P. (2010). Technology for classroom orchestration. In M. S. Khine & I. M. Saleh (Eds.), New science of learning: Cognition, computers and collaboration in education (pp. 525–552). *Springer*. https://doi.org/10.1007/978-1-4419-5716-0_26

Feng, S. (2025). Group interaction patterns in generative AI-supported collaborative problem solving: Network analysis of the interactions among students and a GAI chatbot. *British Journal of Educational Technology*, 56, 2125–2145. https://doi.org/10.1111/bjet.13611

Fischer, F., Kollar, I., Stegmann, K., & Wecker, C. (2013). Toward a script theory of guidance in computer-supported collaborative learning. *Educational psychologist*, *48*(1), 56-66. https://doi.org/10.1080/00461520.2012.748005

Guo, Y., Huang, L., Zhang, C., Li, Q., & Chen, M. (2025). ChatGPT in Education: A Systematic Review of Its Impact on Critical Thinking Skills and Dispositions. *Thinking Skills and Creativity*, 102106. https://doi.org/10.1016/j.tsc.2025.102106

Shoval, D. H. (2025). Artificial intelligence in higher education: Bridging or widening the gap for diverse student populations? *Education Sciences*, 15(5), 637. https://doi.org/10.3390/educsci15050637

Huang, D., Huang, Y., & Cummings, J. J. (2024). Exploring the integration and utilisation of generative AI in formative e-assessments: A case study in higher education. *Australasian Journal of Educational Technology*, 40(4), 1–19. https://doi.org/10.14742/ajet.9467

Irish, A. L., Gazica, M. W., & Becerra, V. (2025). A qualitative descriptive analysis on generative artificial intelligence: Bridging the gap in pedagogy to prepare students for the workplace. *Discover Education*, 4, 48. https://doi.org/10.1007/s44217-025-00435-4

Jia, Y., Li, C., Chan, A., & Li, Q. (2026). Human-Al Collaboration in the STEM Classroom: A Systematic Literature Review of GenAI as a Complement in Higher Education. In International Conference on Technology in Education (pp. 389-401). Springer, Singapore.

Järvelä, S., Nguyen, A., & Hadwin, A. F. (2023). Human and artificial intelligence collaboration for socially shared regulation in learning. British Journal of Educational Technology, 54(5), 1057–1076. https://doi.org/10.1111/bjet.13325

Krause, S., Panchal, B. H., & Ubhe, N. (2024*).* The evolution of learning: Assessing the transformative impact of generative AI on higher education. *arXiv*. https://doi.org/10.48550/arXiv.2404.10551

Law, N., Wang, N., Ma, M., Liu, Z., Lei, L., Feng, S., ... & Tsao, J. (2025). The role of generative AI in collaborative problem-solving of authentic challenges. British Journal of Educational Technology.

Levin, I., Marom, M., & Kojukhov, A. (2025). Rethinking AI in education: Highlighting the metacognitive challenge. *BRAIN: Broad Research in Artificial Intelligence and Neuroscience, 16(Special Issue 1)*, 250–263. https://doi.org/10.70594/brain/16.S1/21

Martínez-Peláez, R., Mena, L. J., Toral-Cruz, H., Ochoa-Brust, A., Potes, A. G., Flores, V., Ostos, R., Pacheco, J. C. R., Félix, R. A., & Félix, V. G. (2025). Can large language models foster critical thinking, teamwork, and problem-solving skills in higher education? A literature review. *Systems*, 13, 1013. https://doi.org/10.3390/systems13111013

Qian, Y. Pedagogical Applications of Generative AI in Higher Education: A Systematic Review of the Field. *TechTrends* **69**, 1105–1120 (2025). https://doi.org/10.1007/s11528-025-01100-1

Parpala, A., & Lindblom-Ylänne, S. (2012). Using a research instrument for developing quality at the university. *Quality in Higher Education*, 18(3), 313–328. https://doi.org/10.1080/13538322.2012.733493

Pham, T. D., Karunaratne, N., Exintaris, B., et al. (2025). The impact of generative AI on health professional education: A systematic review in the context of student learning. *Medical Education*, 59(12), 1280–1289. https://doi.org/10.1111/medu.157

Portocarrero Ramos, H. C., Cruz Caro, O., Sánchez Bardales, E., Quiñones Huatangari, L., Campos Trigoso, J. A., Maicelo Guevara, J. L., & Chávez Santos, R. (2025). Artificial intelligence skills and their impact on the employability of university graduates. *Frontiers in Artificial Intelligence*, 8, Article 1629320. https://doi.org/10.3389/frai.2025.1629320

Ramos, B., & Condotta, R. (2024). Enhancing learning and collaboration in a unit operations course: Using AI as a catalyst to create engaging problem-based learning scenarios. *Journal of Chemical Education, 101*(8), 3246–3254. https://doi.org/10.1021/acs.jchemed.4c00244

Ruiz-Rojas, L. I., Salvador-Ullauri, L., & Acosta-Vargas, P. (2024). Collaborative Working and Critical Thinking: Adoption of Generative Artificial Intelligence Tools in Higher Education. *Sustainability*, 16(13), 5367. https://doi.org/10.3390/su16135367

Salinas-Navarro, D. E., Vilalta-Perdomo, E., Michel-Villarreal, R., & Montesinos, L. (2024). Using Generative Artificial Intelligence Tools to Explain and Enhance Experiential Learning for Authentic Assessment. *Education Sciences*, 14(1), 83. https://doi.org/10.3390/educsci14010083

Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology*, 19(4), 460–475. https://doi.org/10.1006/ceps.1994.1033

Sichterman, B., Noroozi, O., Boetje, J., van Ginkel, S., Khosravi, H., & Versendaal, J. (2025). Supporting peer learning with artificial intelligence: A systematic literature review. Innovations in Education and Teaching International, 62(5), 1648–1664. https://doi.org/10.1080/14703297.2025.2530118

Wang, L. (2023). Metacognitive strategies used in ChatGPT among college students. *Lecture Notes in Education Psychology and Public Media*, *21*, 283-288. https://doi.org/10.54254/2753-7048/21/20230170

Wang, F., & Hannafin, M. J. (2005). Design-based research and technology-enhanced learning environments. *Educational Technology Research and Development, 53*(4), 5–23. https://doi.org/10.1007/BF02504682

Zhao, Z., An, Q., & Liu, J. (2025). Exploring AI tool adoption in higher education: Evidence from a PLS-SEM model integrating multimodal literacy, self-efficacy, and university support. *Frontiers in Psychology*, 16. https://doi.org/10.3389/fpsyg.2025.1619391

Zhou, X., & Schofield, L. (2024). Developing a conceptual framework for Artificial Intelligence (AI) literacy in higher education. *Journal of Learning Development in Higher Education*, (31). https://doi.org/10.47408/jldhe.vi31.1354

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice, 41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2

Zou, D., Xie, H., & Kohnke, L. (2025). Navigating the future: Establishing a framework for educators' pedagogic artificial intelligence competence. *European Journal of Education*, 60, e70117. https://doi.org/10.1111/ejed.70117

Zou, Y., Kuek, F., Feng, W., & Cheng, X. (2025). Digital learning in the 21st century: Trends, challenges, and innovations in technology integration. *Frontiers in Education*, *10*, 1562391. https://doi.org/10.3389/feduc.2025.1562391