Tracing Process Alignment in Human-AI-Human Learning: A Learning Analytics Case of GenAI-Assisted Preparation and Peer Feedback[*]

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Abstract

As generative artificial intelligence (GenAI) becomes embedded in learning activities, learners increasingly engage in multi-phase human–AI–human learning sequences, where AI-supported individual preparation precedes peer collaboration. While prior research has examined learning outcomes and perceptions of GenAI use, less attention has been paid to how ideas developed during human–AI interaction are taken up, transformed, or set aside in subsequent human–human collaboration—particularly from a process-oriented learning analytics perspective. This paper presents a methodological and analytical demonstration for tracing process alignment across such learning sequences, focusing on GenAI-assisted preparation followed by peer feedback dialogue. Using empirical data from student teachers (36 GenAI prompt logs and 18 dyadic peer dialogues), this study illustrates an analytic pipeline that integrates semantic similarity analysis, behavioral coding of feedback roles, sequence clustering, and compact hidden Markov models (HMMs). Rather than evaluating the effectiveness of GenAI or making causal claims, our analyses descriptively characterize how preparatory human–AI interactions relate to subsequent collaborative processes. The results illustrate two distinct interaction profiles: a socially oriented, praise-driven feedback mode and an elaboration-oriented mode characterized by higher semantic alignment between GenAI prompts and dialogue utterances. These profiles highlight different ways in which AI-supported preparation may be appropriated within peer dialogue. We position this work as a contribution to the GenAI–Learning Analytics community by offering reusable analytic tools and conceptual framing for examining process-level dynamics of human–AI collaboration across learning phases.

Keywords

Human-AI collaboration, Peer feedback, Process alignment, Learning analytics, Generative AI, Semantic similarity, Sequential analysis

1. Introduction

Generative Artificial Intelligence (GenAI) is increasingly integrated into education, reshaping how learners prepare, reason, and collaborate. Beyond providing answers, GenAI often serves as a preparatory partner, helping learners articulate ideas, explore alternatives, and rehearse reasoning before social interaction. Consequently, learning activities involve multi-phase human–AI–human sequences, where AI-supported preparation precedes peer dialogue. Understanding these connections is a key challenge for learning analytics and learning sciences.

Peer feedback dialogue provides a rich context for examining this handover. It is a complex process of diagnosis, planning, reasoning, and action [1], requiring students to identify issues, evaluate ideas, elaborate reasoning, and reach consensus—combining divergent and convergent thinking. In the AI era, GenAI rapidly generate multiple solutions and personalized information [2, 3], potentially enriching peer feedback by expanding idea pools.

Yet little is known about how GenAI-assisted preparation aligns with subsequent peer dialogue. Most research has focused on outcomes, perceptions, or AI-generated content quality, while less

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attention has been paid to how ideas from human–AI interaction are taken up, transformed, or abandoned in human collaboration. This gap limits our ability to design and evaluate productive partnerships, as GenAI's educational value may lie not in output alone but in how they are appropriated within collaborative processes. In response, this study presents a methodological demonstration tracing alignment between GenAI preparation and peer dialogue using student teacher data. Our pipeline integrates:

- Behavioral coding to capture roles enacted by feedback providers and receivers.
- Semantic similarity analysis to quantify alignment between GenAI prompts and dialogue utterances.
- Sequential analysis and clustering to identify distinct patterns of feedback interaction.

We frame our contribution as methodological, offering tools to illuminate human–AI collaborative processes and their connections to peer dialogue. We do not claim causal effects but examine associations and co-occurring patterns, introducing "prompt–dialogue process alignment" as an analytic construct for future controlled studies. This study explores:

- RQ1. How can semantic similarity between GenAI-assisted preparation and peer dialogue serve as an indicator of process alignment in human–AI–human learning sequences?
- RQ2. What collaborative interaction patterns emerge in peer feedback dialogue, and how are these patterns associated with differences in preparatory alignment?

By integrating semantic, behavioral, and temporal analyses, this work contributes to the GenAI –Learning Analytics (LA) community by demonstrating how LA methods can illuminate the process-level dynamics of human–AI collaboration across phases, supporting future empirical, design-oriented, and ethical inquiry into productive human–AI partnerships.

2. Background

2.1. GenAI-Assisted Preparation as Human-AI Interaction

Prompt engineering—a dialogic, co-creative skill—requires detecting LLM errors, iterating prompts, and evaluating effectiveness [4, 5]. Its iterative nature resembles drafting and revising creative work [3]. GenAI shifts human–AI relations from competition to synergy by generating multiple options for human selection [6]. Human judgment and divergent thinking remain crucial [7]. From this perspective, GenAI-assisted preparation may function as a form of epistemic rehearsal. Dynamic prompting provides immediate, personalized feedback and diverse solutions [2, 3], yet its influence on later collaboration is underexplored.

Prior work shows GenAI supports divergent thinking, alternative representations, and external scaffolds [8, 9]. Iterative prompt–response cycles help learners test hypotheses, refine queries, and rehearse evaluative judgments, potentially preparing them for collaboration. However, links between preparation and peer dialogue remain underexplored. This study therefore examines prompt–dialogue alignment via semantic similarity, defining human–AI interaction as structured preparation with GenAI through iterated prompts to articulate goals, explore ideas, and refine understanding before peer dialogue.

2.2. Peer Feedback Dialogue as a Collaborative Process

Feedback effectiveness depends on engagement [10]. Dialogue enhances clarification [11] and combining written and oral modes deepens understanding [12]. Reciprocal interaction allows providers and receivers to resolve ambiguity and refine tasks [13]. Research on proactive recipience emphasizes the agency of receivers in shaping dialogue through behaviors such as verification, explication, and idea generation [13, 14].

Elaborated feedback (e.g., questions, concerns, suggestions) drives collaborative knowledge building [15]. Receivers' responses deepen understanding, support retention, and promote transfer [16], while helping providers refine domain knowledge and evaluation skills [13]. These behaviors shape dialogue flow and indicate cognitive and social engagement. From a learning analytics perspective, these roles can be operationalized through fine-grained behavioral coding and examined as sequences over time.

2.3. Present Study

Most learning analytics focus on outcomes rather than multi-phase alignment. In this study, peer feedback dialogue serves as the site where preparatory ideas may be taken up, transformed, or resisted. By analyzing feedback roles and their temporal organization, we examine how preparatory alignment relates to different modes of collaborative interaction. To address this, we integrate:

- Semantic similarity modeling. Sentence-BERT embeddings [17] quantify proximity between GenAI prompts and peer utterances. Given the Chinese language context, we used the Sentence-BERT Chinese model (RTB3) [18].
- Sequence clustering and modeling. Optimal matching with Ward's clustering identifies discourse profiles; compact hidden Markov models (HMMs) summarize feedback state transitions descriptively. HMMs are treated as representations of observable interaction flow, not latent cognitive states.

3. Methods

3.1. Contexts and Participants

Fifty-four third-year student teachers in an educational technology course at a large Asian public university participated. The activity, embedded in regular instruction, comprised: Step1-Lesson Plan Design Phase: submission of one secondary physics lesson plan. Step 2-GenAI-assisted Preparation Phase (Human-AI Interaction): 20 minutes refining own plan and 20 minutes evaluating a peer's plan using Wenxinyiyan (ERNIE). Step 3-Dialogue and Feedback Reflection Phase (Human-Human Collaboration): 30 minutes of paired discussion on exchanged feedback, articulating acceptance, rejection and underlying reasoning. Step 4-Final Revision Phase (not analyzed): 10 minutes revising and resubmitting plans.

3.2. Data Collection and Analysis

After excluding incomplete entries, the final dataset comprised 36 screen recordings of the GenAI-assisted preparation phase and 18 audio recordings of peer dialogues (18 pairs). All GenAI prompts were collected, cleaned, and segmented for analysis. Analytic choices targeted alignment, role enactment, and temporal organization. These methods serve descriptive and illustrative functions rather than explanatory or causal ones.

For feedback and meta-feedback, qualitative content analysis categorized moves by role: givers (cognitive features, [19] and receivers (proactive roles, [13]; praise was coded for both [20] (see Table 1). Audio recordings were manually transcribed, anonymized (S1–S36), and off-topic content removed, 36,185 words remained. Two coders annotated transcripts (one full, one 20%), achieving 85% agreement. In total, 1,317 feedback moves were identified. Code solutions and high-solution figures are available via OSF: https://osf.io/6gqrd/?view_only=6052567c2509418799308b57f8802ee9

- RQ1: Semantic similarity analysis. Alignment was computed by comparing each participant's GenAI prompts with dialogue utterances (provider vs. receiver). Sentence-BERT (RTB3 Chinese model); [18] generated embeddings; cosine similarity scores (0–1) were correlated (Spearman) with behavioral features. Significant results were visualized in Python.

- RQ2: Feedback dynamics. Dialogues were transformed into coded sequences. Using TraMineR [21] and Cluster [22] in R, optimal matching and Ward's clustering yielded a two-cluster solution. For each cluster, a two-state hidden Markov model (seqHMM) [23] was fitted and evaluated by AIC/BIC. Emission probabilities indicated dominant behaviors; transition probabilities summarized feedback flow. This modeling compactly visualized temporal dynamics, complementing clustering and correlational analyses.

Table 1
Coding Scheme of Feedback Features

Role	Dimension	Code	Examples
Feedback giver	Cognitive dimension (problem)	Problem identification	"Let me tell you, look, shouldn't the target subject be the student? This is wrong. Right, did your teacher say that?"
		Problem elaboration	"Yes, for example, the subject of the goal should be students. When writing teaching goals, you should follow the curriculum standards."
	Cognitive dimension (constructiveness)	Suggestion	"Okay, I'll help you change it."
		Solution	"There are many small points on each point. But I think each one can be just a sentence."
Feedback receiver	Reaction to feedback	Receiver as respondent	"Um." (In Chinese, one meaning of this sentence is attention has been paid.)
		Receiver as verifier	"Oh, then don't have noun "students" this way. For example, sentences should have verbs like "master" and "understand"."
		Receiver as explicator	"The first is knowledge, the second is method, and the third is emotion."
		Receiver as negotiator	"I don't think it matters."
		Receiver as seeker	"Any questions?"
		Receiver as generator	"In fact, you can also revise the homework part. There are final exercises. There can involve exploration and practice activities."
Feedback giver or receiver	Praise comments	Praise	"Nice, you are so smart, I didn't think of that."

4. Results

4.1. Descriptive Features

Descriptive statistics (Table 2) show that feedback providers most often offered Solutions (M = 8.67) and Problem identification (M = 4.28), while receivers most frequently acted as Explicators (M = 6.28) and Respondents (M = 4.22). Praise appeared in both roles. These patterns indicate dialogues emphasized elaboration and clarification, aligning with the activity's design. Semantic similarity values averaged 0.59–0.61, reflecting moderate alignment between GenAI prompts and subsequent peer utterances.

Table 2

Descriptive Statistics for Individual Feedback Features

Behaviors features	M(SD)	Behaviors features	M(SD)
As receiver VS prompts	0.59 (0.17)	Solution	8.67 (7.4)
As giver VS prompts	0.61 (0.15)	Receiver as respondent	4.22 (5.18)
dialogue_words	1005.31 (774.19)	Receiver as verifier	3.14 (3.79)
dialogue_turns	36.58 (21.91)	Receiver as explicator	6.28 (6.26)
n_prompt_turn	6.31 (3.35)	Receiver as negotiator	0.78 (1.2)
Problem identification	4.28 (3.7)	Receiver as seeker	1.17 (1.68)
Problem elaboration	3.5 (3.55)	Receiver as generator	1.89 (2.05)
Suggestion	1.64 (1.87)	Praise	1.39 (1.61)

Note. "As receiver vs. prompts" and "As giver vs. prompts" denote similarity scores (0 = no similarity, 1 = identical meaning) between participants' utterances in each role and their GenAI prompts.

4.2. RQ1: Associations Between Prompt-Dialogue Alignment and Elaboration

Sequential analysis showed two collaborative patterns: Cluster 1 (6 activities) and Cluster 2 (12 activities) (Figure 1).

In Figure 2 (left), Cluster 1 shows a correlation of 0.65 between As receiver vs. prompts and Receiver as verifier. Praise also correlates with dialogue turns (0.73) and Receiver as explicator (0.75). Cluster 2 (right in Figure 2) illustrates broader associations: As receiver vs. prompts correlates with Receiver as verifier (0.59), explicator (0.57), generator (0.48), dialogue words (0.61), and dialogue turns (0.44). Additionally, As giver vs. prompts correlates with Receiver as verifier (0.41). Based on these relationships, Cluster 1 is labeled the "high praise cluster" and Cluster 2 the "high alignment cluster." Both highlight links between prompt similarity and verification behaviors, but Cluster 2 also shows positive correlations with dialogue length and elaborative roles (explication, generation).

Linking Alignment to Feedback Dynamics. Comparing clusters characterized notable patterns: 1. Both clusters associate alignment with Receiver as verifier, suggesting semantic overlap fosters clarification. 2. Only Cluster 2 links alignment with elaborative measures (length, generator, explicator). 3. Cluster 1 relies on praise-driven transitions, while Cluster 2 emphasizes idea-driven transitions. Thus, process alignment supports elaboration more strongly in Cluster 2, whereas

Cluster 1 reflects social or affective regulation. Further sequencing analysis is needed to examine feedback state transitions.

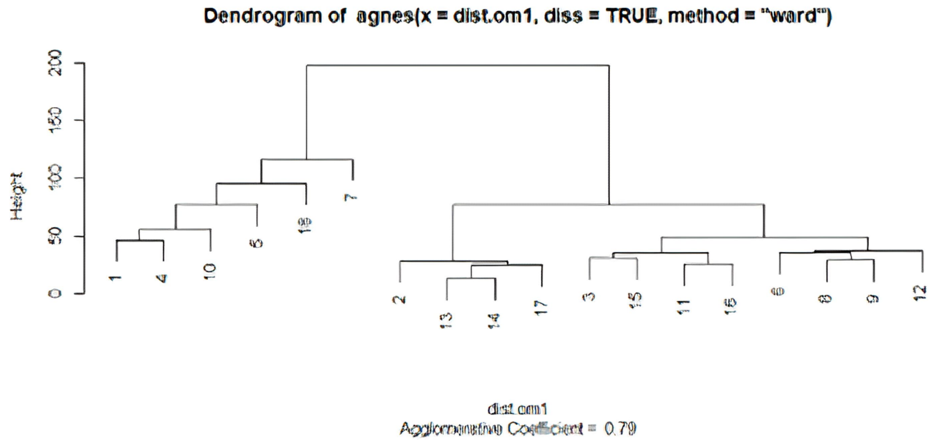

Figure 1: Ward's Clustering Results for the 18 Feedback Sequences.

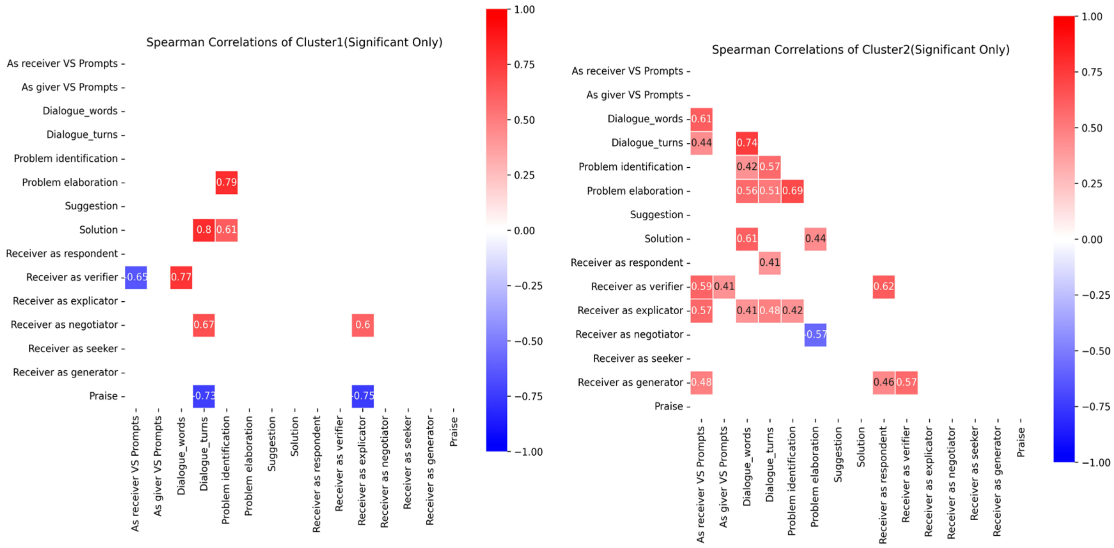

Figure 2: Spearman Correlations between Document Similarity and Feedback Fatures of Cluster 1(Left) and Cluster 2 (Right).

4.3. RQ2: HMM-Based Sequential Summaries of Feedback Dynamics

To capture temporal dynamics, two-state HMMs were fitted for each cluster (Figure 3), selected by optimal fit indices (AIC, BIC, log-likelihood). The models provide descriptive summaries with emission probabilities above 0.05.

Cluster 1 (high praise, Figure 3 left). State 1 was dominated by Praise (70.49%), with initial probability near 100%, transitioning to State 2 (88.73%) and back (93%). State 2 featured Receiver as negotiator (64.7%) and Receiver as generator (25.01%). Frequent bidirectional transitions suggest short cycles of affective regulation followed by negotiation or idea generation, with praise sustaining dialogue. Cluster 2 (high alignment, Figure 3 right). State 1 comprised Receiver as generator (42.2%), Praise (25.4%), Explicator (15.4%), and Seeker (14.69%). State 2 included Generator (36.4%), Problem elaboration (24.4%), Explicator (16.5%), and Praise (12.2%). The initial probability of State 1 was nearly 100%, with limited transitions (8.6% to State 2; 14.9% back). Cluster 2 dialogues showed diverse elaboration chains and reciprocal knowledge-building turns, with Receiver as generator proportionally higher than in Cluster 1.

Summary. Preparatory GenAI prompting behaviors co-occur with distinct collaborative patterns: Cluster 1 reflects praise-driven regulation, while Cluster 2 demonstrates sustained elaboration through extended explanation, clarification, and idea generation. Overall, GenAI-assisted preparation may support epistemic readiness for elaborative meaning-making.

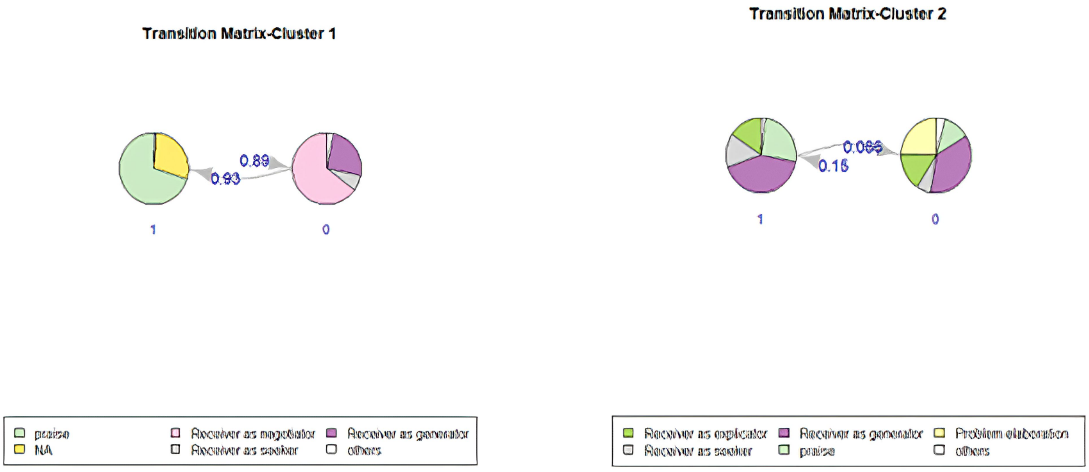

Figure 3: Feedback State Transition of Cluster 1(Left) and Cluster 2 (Right).

5. Discussion

This study illustrates a process-analytic approach to examining how GenAI-assisted preparation relates to peer feedback dialogue in human–AI–human learning sequences. Rather than testing causal hypotheses, we focused on process alignment—semantic and interactional connections between preparatory human–AI interaction and collaborative dialogue. Findings provide several insights for the GenAI–LA community.

Process alignment as a lens on Human-AI collaboration. Semantic alignment between GenAI prompts and dialogue utterances functioned as a process signal indicating how preparatory formulations carried into peer interaction. Higher alignment co-occurred with clarification and elaboration, particularly verification and explication, suggesting GenAI-assisted preparation may shape the linguistic and conceptual resources available for dialogue. Alignment was not consistently linked to deeper problem elaboration, underscoring that GenAI aids breadth and clarity but does not replace human judgment or contextual reasoning [2, 3]. Alignment should thus be seen as a process signal, not learning itself.

Feedback receivers as the Human-AI interface. Receiver roles proved pivotal in shaping dialogue trajectories. Verification, explication, and generation behaviors sustained elaboration, highlighting receivers' agency in integrating, challenging, or transforming AI-supported preparation. This aligns with proactive recipience [14] and suggests productive partnerships require attention not only to prompting but also to how learners appropriate AI-generated ideas. LA that foreground receiver roles can enrich accounts of agency and responsibility in GenAI-supported learning.

Multiple modes of handover from AI preparation to collaboration. Two profiles emerged: a socially oriented, praise-driven mode and an elaboration-oriented, high-alignment mode. In some cases, alignment supported social regulation and rapport; in others, it co-occurred with sustained explanatory and generative activity. These profiles should not be ranked but recognized as diverse forms of human–AI–human coordination shaped by norms, roles, and purposes. Such diversity cautions against one-size-fits-all assumptions about GenAI's role in collaboration.

Methodological contributions to GenAI-LA community. This study shows how semantic similarity, sequence clustering, and compact HMMs can be combined to trace alignment, characterize interaction profiles, and summarize temporal dynamics without latent-state inference or causal claims. The pipeline shifts attention from outcome prediction to process-level modeling of human–AI collaboration. Its transferability across domains and tools supports comparative, design-based, and theory-building research.

6. Implications and Limitations

Contributions to GenAI-LA. This work contributes a process-oriented analytic pipeline integrating semantic similarity, behavioral coding, sequence clustering, and compact HMMs to examine alignment, interaction profiles, and temporal dynamics in human–AI collaboration. The approach extends LA beyond outcome-focused evaluation toward modeling the flow and handover of ideas across learning phases. Conceptually, we introduce process alignment as a construct capturing how AI-supported formulations intersect with collaborative discourse, offering a middle ground between treating GenAI as an independent intervention and ignoring its role in shaping interaction.

Implications for designing Human-AI collaborative learning. Findings suggest GenAI functions best as a preparatory collaborator supporting epistemic readiness rather than providing definitive solutions. Educational designs should: 1. Scaffold intentional prompting to externalize reasoning prior to collaboration; 2. Encourage critical evaluation and selective integration of AI-generated ideas; 3. Support learners—especially feedback receivers—in articulating, verifying, and transforming preparatory insights during dialogue. Such designs foreground human agency and responsibility in human–AI partnerships.

Implications for peer feedback pedagogy. Receiver roles proved central, underscoring the importance of proactive recipience. Peer feedback pedagogy may benefit from: 1. Explicitly training receivers to verify, explicate, and generate alternatives; 2. Using GenAI to support both feedback providers and receivers in preparation; 3. Designing transitions from individual AI-supported work to collaborative dialogue. These implications align with calls to reconceptualize feedback as dialogic and agentic.

Limitations. This exploratory study has constraints: 1. Single-group design: results are associate, not causal; future work should compare preparation methods. 2. Moderate sample size: 18 dialogues enable rich analysis but limit generalizability. 3. Semantic similarity proxy-lexical overlap may not capture deeper conceptual alignment; complementary measures are needed. 4. Context specificity: participants were student teachers; other domains may differ. Despite these constraints, the study provides an exploration for examining cross-phase human–AI–human learning. Future research should extend the pipeline to other domains and tools, integrate design-based interventions, and explore intentional prompting, structured reflection, and scaffolded transitions to design responsible and equitable human–AI partnerships.

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Declaration on Generative AI

During the preparation of this work, the author used ChatGPT in order to: Grammar and spelling check.

References

[1] E. Er, Y. Dimitriadis, D. Gašević, A collaborative learning approach to dialogic peer feedback: a theoretical framework, Assessment & Evaluation in Higher Education 46 (2021) 586–600. doi:10.1080/02602938.2020.1786497.

[2] P. Zhang, G. Tur, A systematic review of ChatGPT use in K-12 education, European Journal of Education 59 (2024) e12599. doi:10.1111/ejed.12599.

[3] S. Habib, T. Vogel, E. Thorne, Student perspectives on creative pedagogy: Considerations for the Age of AI, Thinking Skills and Creativity 56 (2025) 101767. doi:10.1016/j.tsc.2025.101767.

[4] J. Oppenlaender, R. Linder, J. Silvennoinen, Prompting AI art: An investigation into the creative skill of prompt engineering, International Journal of Human–Computer Interaction 41 (2025) 10207–10229. doi:10.1080/10447318.2024.2431761.

[5] J. D. Zamfirescu-Pereira, R. Y. Wong, B. Hartmann, Q. Yang, Why Johnny can't prompt: how non-AI experts try (and fail) to design LLM prompts, in: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, ACM, 2023, pp. 1–21. doi:10.1145/3544548.3581388.

[6] J. Rafner, R. E. Beaty, J. C. Kaufman, T. Lubart, J. Sherson, Creativity in the age of generative AI, Nature Human Behaviour 7 (2023) 1836–1838. doi:10.1038/s41562-023-01751-1.

[7] L. Markauskaite, R. Marrone, O. Poquet, S. Knight, R. Martinez-Maldonado, S. Howard, G. Siemens, Rethinking the entwinement between artificial intelligence and human learning: What capabilities do learners need for a world with AI?, Computers and Education: Artificial Intelligence 3 (2022) 100056. doi:10.1016/j.caeai.2022.100056.

[8] Y. H. Chiu, C. C. Chen, Elevating and Sharpening Convergent Thinking: The Potential of Generative AI for Creative Professionals, SSRN Preprint (2024). doi:10.2139/ssrn.4911494.

[9] M. Urban, F. Děchtěrenko, J. Lukavský, V. Hrabalová, F. Svacha, C. Brom, K. Urban, ChatGPT improves creative problem-solving performance in university students: An experimental study, Computers & Education 215 (2024) 105031. doi:10.1016/j.compedu.2024.105031.

[10] R. A. de Kleijn, Supporting student and teacher feedback literacy: an instructional model for student feedback processes, Assessment & Evaluation in Higher Education 48 (2023) 186–200. doi:10.1080/02602938.2021.1967283.

[11] M. F. Chow, Understanding student perspectives on peer feedback: Written versus video versus face-to-face dialog, Active Learning in Higher Education (2024). doi:10.1177/14697874241301263.

[12] C. Armengol-Asparó, C. Mercader, G. Ion, Making peer-feedback more efficient: What conditions of its delivery make the difference?, Higher Education Research & Development 41 (2022) 226–239. doi:10.1080/07294360.2020.1840527.

[13] Q. Zhu, J. To, Proactive receiver roles in peer feedback dialogue: Facilitating receivers' self-regulation and co-regulating providers' learning, Assessment & Evaluation in Higher Education 47 (2022) 1200–1212. doi:10.1080/02602938.2021.2017403.

[14] N. E. Winstone, R. A. Nash, M. Parker, J. Rowntree, Supporting learners' agentic engagement with feedback: A systematic review and a taxonomy of recipience processes, Educational Psychologist 52 (2017) 17–37. doi:10.1080/00461520.2016.1207538.

[15] J. S. Tan, W. Chen, Peer feedback to support collaborative knowledge improvement: What kind of feedback feed-forward?, Computers & Education 187 (2022) 104467. doi:10.1016/j.compedu.2022.104467.

[16] B. Finn, R. Thomas, K. A. Rawson, Learning more from feedback: Elaborating feedback with examples enhances concept learning, Learning and Instruction 54 (2018) 104–113. doi:10.1016/j.learninstruc.2017.08.007.
[17] N. Reimers, I. Gurevych, Sentence-BERT: Sentence embeddings using siamese BERT-networks, arXiv preprint arXiv:1908.10084 (2019).
[18] Y. Cui, W. Che, T. Liu, B. Qin, Z. Yang, Pre-training with whole word masking for Chinese BERT, IEEE/ACM Transactions on Audio, Speech, and Language Processing 29 (2021) 3504–3514. doi:10.1109/TASLP.2021.3124365.
[19] W. Chen, Q. Lyu, J. Su, How more-improvement and less-improvement groups differ in peer feedback giving and receiving practice—an exploratory study, Instructional Science 53 (2025) 27–47. doi:10.1007/s11251-024-09667-7.
[20] Y. Wu, C. D. Schunn, From feedback to revisions: Effects of feedback features and perceptions, Contemporary Educational Psychology 60 (2020) 101826. doi:10.1016/j.cedpsych.2019.101826.
[21] A. Gabadinho, G. Ritschard, N. S. Müller, M. Studer, Analyzing and visualizing state sequences in R with TraMineR, Journal of Statistical Software 40 (2011) 1–37. doi:10.18637/jss.v040.i04.
[22] M. Maechler, Cluster: cluster analysis basics and extensions, R package version 2.0.7-1 (2018). Available at: https://cir.nii.ac.jp/crid/1370290617548437512.
[23] S. Helske, J. Helske, Mixture hidden Markov models for sequence data: The seqHMM package in R, Journal of Statistical Software 88 (2019) 1–32. doi:10.18637/jss.v088.i03.