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EDITORIAL

AI-assisted feedback: students' feedback perceptions, emotions, actions, and literacies

This collection is the first of a two-part Special Issue on *AI-assisted feedback: students' feedback perceptions, emotions, actions, and literacies*. It arrives at a time when both theory and practice are rapidly expanding, and when new generative-AI technologies invite educators and researchers to rethink the very essence of 'feedback.'

Part I brings together seven papers – six with first-hand empirical data and one meta-analysis. Together, they offer early evidence and conceptual contours of this shifting landscape. Part II will revisit these discussions and weave together insights from forthcoming articles trying to paint a fuller picture of AI-assisted feedback across contexts.

Step 1: descriptive synthesis: seven windows on AI-assisted feedback

These papers in Part I offer a timely and multifaceted glimpse of how researchers across the globe are grappling with AI-assisted feedback in classrooms. Six papers examine data from classrooms, language-learning contexts, and teacher-education programmes in China, Turkey, Singapore, Norway, and Sweden in 2025. One paper synthesises data from 41 studies spanning 2010–2024, offering a long view of this unfolding conversation. Table 1 presents a brief overview of these seven contributions before we elaborate on each study in turn. Together, these studies lay the foundation for understanding how AI technologies are used, adapted, and interpreted as new feedback partners in learning.

The first study, Lu and Ba (2025), ran a quasi-experiment in China with 108 pre-service teachers (53 in the experimental group, 55 in the control group). The experimental group, which used GPT-4 to get feedback and support their inquiry-based online discussions, showed higher behavioural engagement, social engagement, and oral-presentation performance than the control group. However, cognitive load and emotional engagement did not differ across groups. These findings show how AI-assisted feedback in inquiry-based online discussions can support students' collaborative meaning-making without raising cognitive demands.

Yıldız et al. (2025) counterbalanced two-task study assessed the argumentative writing of 59 EFL university students in Turkey. They received both human-tutor and GenAI feedback. While both improved their writing, human-tutuor feedback boosted linguistic accuracy and mechanics more, pointing to the limitations of GenAI tools used in this study for aiding writing for further exploration in future studies.

Ding and Song (2025) ventured into a metaverse and explored a multimodal AI-assisted feedback system that blended GPT-4, Mixtral, diffusion models, and retrieval-augmented generation. In their quasi-experiment of 67 Chinese undergraduates (34 experimental, 33 control), experimental students in the AI-supported condition reported higher perceived usefulness, stronger engagement, and improved

Table 1. Summary of the seven studies in Part I of the Special Issue.

#	Author (year)	Research scope (concise focus)	Region/country	Sample and context	Key methods/design	Key takeaway
1	Lu and Ba (2025)	Examines the effects of GPT-4-mediated group feedback on engagement and performance in inquiry discussions.	China	*n* = 108 pre-service teachers (Exp = 53; Ctrl = 55); 8 groups/class (6–7 students/group).	Quasi-experimental with intact classes; GPT-4–mediated group-level feedback embedded in inquiry-based online discussions; 40-min discussions + group presentations; MANOVA/ANCOVA for engagement and performance; interaction coding for feedback use patterns.	AI-mediated group feedback may enhance collaborative engagement and group performance without adding cognitive burden.
2	Yıldız et al. (2025)	Compares human-tutor and GenAI feedback on university students' argumentative writing performance.	Turkey	*n* = 59 EFL university students; counterbalanced two-task crossover.	Counterbalanced quasi-experimental within-participant crossover; students alternated between human teacher and GenAI feedback across two writing tasks; draft-based writing scored using a 5-dimension analytic rubric; mixed-design ANCOVA controlling for initial draft performance.	Human and AI feedback both support improvement, with human feedback stronger for language-sensitive aspects.
3	Ding and Song (2025)	Investigates a multimodal GAI scaffold's influence on perceptions, engagement, and writing performance.	China	*n* = 67 undergraduates (Exp = 34; Ctrl = 33); metaverse-based writing course.	*Quasi-experimental pre/post design with experimental vs. control group; experimental group used GenAI as a cognitive scaffold in a metaverse environment; self-report perception and engagement measures; writing outcomes analysed via multivariate methods (e.g., MANCOVA).*	A multimodal scaffold integrating several AI models may bolster engagement and writing outcomes when embedded in a structured learning environment.
4	Khor et al. (2025)	Explores predictors of students' acceptance and intention to use GenAI feedback in programming education.	Singapore	*n* = 60 upper-secondary computing students (age 15–16).	Predictive correlational study grounded in TAM; survey-based measures of perceived usefulness, ease of use, subjective norms, and intention to use GenAI feedback; regression analyses; no experimental manipulation of feedback.	Acceptance of AI-assisted feedback is shaped mainly by perceived usefulness, subjective norms, and ease of use.

(*Continued*)

Table 1. Continued.

#	Author (year)	Research scope (concise focus)	Region/country	Sample and context	Key methods/design	Key takeaway
5	Gamlem et al. (2025)	Examines pre-service teachers' experiences, beliefs, and concerns regarding the use of GenAI in education.	Norway	Survey n = 209 pre-service teachers; + interview n = 11 (5 novices, 6 experienced).	Explanatory sequential mixed-methods design: quantitative survey first followed by semi-structured interviews analysed using inductive thematic analysis.	Pre-service teachers recognise potential benefits but emphasise trust, clarity, and responsible implementation.
6	Otaki et al. (2025)	Investigates NNES students' and educators' perceptions of AI feedback, with emphasis on dialogic and ethical aspects.	Sweden	n = 26 (17 NNES students + 9 educators).	Study 1: focus group interviews analysed via reflexive thematic analysis; Study 2: Epistemic Network Analysis (ENA) comparing epistemic frames of students and educators using an ethics-extended codebook.	Learners and educators emphasise different values, especially regarding efficiency, emotion, and ethics.
7	Kaliisa et al. (2025)	Synthesises performance and perception outcomes from earlier AI-assisted feedback studies (2010–2024).	Multi-region (41 studies)	41 studies; N = 4813 learners.	Random-effects meta-analysis comparing AI vs human feedback; effect sizes adjusted for dependence; subgroup and moderator analyses across outcome types and study features.	Earlier evidence shows no consistent performance advantage of AI over human feedback; hybrid and context-sensitive models appear most promising.

Note. Readers are encouraged to consult the original studies for detailed descriptions of research design, analytical procedures, contextual constraints, and nuanced findings that cannot be fully captured in a summary table.

rubric-based writing. These results show how carefully integrated multimodal systems can enhance active learning and task performance.

Turning from learning outcomes to the factors influencing technology adoption, Khor et al. (2025) used a Technology-Acceptance-Model and analysed how 60 upper-secondary programming students in Singapore perceived and intended to use feedback from MyBotBuddy, a school-developed GenAI chatbot. Perceived usefulness, subjective norms, and enjoyment predicted students' intention to use AI-assisted feedback. These findings highlight key motivational conditions that may facilitate the adoption of AI-generated feedback in digital learning environments.

Two studies examined teacher education. In Gamlem et al. (2025), mixed-methods study of 209 Norwegian pre-service teachers showed generally positive views of GenAI with concerns about trust, fairness, and academic integrity. Those with more digital confidence or AI familiarity had more positive beliefs. Meanwhile, Otaki et al.'s (2025) complementary qualitative–quantitative ethnographic comparison examined 17 non-native English-speaking students and nine teachers at a university. Thematic analysis and epistemic network analysis showed that students often valued immediacy and emotional neutrality, but educators emphasised ethical reliability, quality assurance, and holistic judgement. The two studies indicate that divergent priorities between students and educators—particularly regarding efficiency, emotional engagement, and ethical accountability—are likely to influence how AI-assisted feedback is perceived, accepted, and enacted within teacher education contexts.

Kaliisa et al.'s (2025) meta-analysis of 41 studies (N = 4813) between 2010 and January 2024, before the rapid expansion of generative-AI tools, showed no significant differences in the impact of AI-generated versus human-generated feedback on performance or perception. Still, AI systems, feedback types, and task designs varied substantially. Hybrid human–AI arrangements often yielded better outcomes. In contrast, the empirical studies included in this Special Issue draw on recent generations of AI-assisted feedback tools implemented in 2025, thereby extending the evidence base to contemporary generative AI contexts.

Across these seven contributions, several patterns emerge. First, AI-assisted feedback is often implemented at the task and process levels, supporting idea generation, linguistic revision, debugging, and explanation. Second, unlike the meta-analysis of older studies, the 2025 field studies reported short-term perceptual or behavioural benefits (e.g. usefulness, engagement, or intention to use) and moderate performance gains in structured tasks. Third, the existing studies place comparatively less attention to feedback oriented towards self-regulation or self-reflection, ethical trust, learner autonomy, and longer-term developmental trajectories. These observations suggest that future research may benefit from greater attention to feedback processes related to self-regulation and self-reflection, ethical trust, learner autonomy, and longer-term developmental trajectories, which remain comparatively underexplored in the current evidence base.

Step 2: evaluative overview: relating the 2025 evidence to the framework of Ba et al. (2025)

While Step 1 summarises what the seven studies in this Special Issue collectively report, a complementary perspective helps clarify how these contributions relate to broader conceptual discussions surrounding AI-assisted feedback. Because the studies differ in design, context, and focus, a structured interpretive lens enables a clearer view of the particular dimensions of feedback each paper speaks to. For this purpose, we draw on the conceptual framework presented in the recent systematic review by Ba et al. (2025).

Why this framework offers a useful lens?

The framework proposed by Ba et al. (2025), based on a systematic review of 129 studies, integrates elements from the Self-System Model of Motivational Development (SSMMD) and Self-Determination Theory (SDT) to describe AI-assisted feedback across several interconnected layers: (a) the macro level refers to AI mechanisms, data flows, and ethical environments; (b) the meso level describes pedagogical feedback foci from task and process to self-regulation and self; (c) the micro level outlines different degrees of feedback complexity; and (d) the learner pathway examines how feedback conditions shape learners' perceptions, actions, and outcomes. Designed to organise diverse studies of AI-assisted feedback, this framework is a descriptive reference for identifying how these 2025 studies fit into the AI-assisted feedback ecosystem. Using this model as a descriptive organising tool, Table 2 summarises how each study relates to selected macro, meso, micro, and learner-pathway dimensions.

Synthesis of the mapping results

The alignment of the 2025 studies with the Ba et al. (2025) framework reveals patterns in contemporary AI-assisted feedback studies. At the macro level, these studies describe AI mechanisms (e.g. GPT-4, school-developed chatbots, or multimodal systems), with occasional attention to ethical considerations (e.g. privacy, bias, responsible use). Hence, they offer context for understanding how different AI systems function within learning environments.

At the meso level, all studies address task- or process-oriented feedback (e.g. generate ideas, revise writing, explain codes, plan lessons). This suggests that current studies focus on immediate and observable aspects of feedback rather than self-regulation or self-related feedback.

At the micro level, the studies offer intermediate feedback complexity – contextualised guidance, explanations, and suggestions – rather than more elaborated, reflective forms of feedback. Human- versus AI-delivered feedback in Yıldız et al. (2025) offers a notable explicit contrast. The AI-assisted feedback systems in these studies often offer directive or supportive feedback without extending into deeper metacognitive prompting.

Regarding the learner pathway, these studies used different variables. Some captured perceptions (e.g. usefulness, trust, attitudes). Others assessed actions or action proxies (e.g. engagement, intention to use), and still others measured performance outcomes. Few traced sequential relationships across the multiple stages of pathways. This pattern suggests that empirical attention has focused more on early-stage learner responses than on longer-term behavioural or developmental trajectories.

Closing remarks

Taken together, the studies in Part I of this special issue illustrate how current AI-assisted feedback research relates to different aspects of Ba et al.'s (2025) conceptual model. Most empirical contributions engaged with the task–process levels of feedback with intermediate feedback complexity, reflecting how AI is used in teaching and

Table 2. Indicative alignment of 2025 studies with components of the Ba et al. (2025) framework.

Study (2025)	Macro – AI mechanism/ethical context	Meso – pedagogical focus	Micro – feedback complexity	Learner pathway – variables explicitly measured	Editorial observation on relation to the framework
Lu and Ba (2025)	GPT-4 chatbot; human-mediated classroom use; ethics noted.	Task + Process (idea generation and group synthesis).	*Intermediate* (contextual, directive feedback).	Cognitive load → behavioural/social engagement → oral performance.	The design *engages partially with multiple levels* and provides an example of sequential links in the learner pathway.
Yıldız et al. (2025)	GPT-4 CLEAR-path prompts vs. human tutor; ethical parity.	Task + Process (analytic writing rubric).	*Intermediate* (AI)/*Elaborated* (Human).	Writing scores (Outcome).	The study *illustrates potential relations* between feedback complexity and performance outcomes, without complementary data on learners' perceptions and actions.
Ding and Song (2025)	Multimodal GAI scaffold (GPT-4 + Mixtral + Diffusion + RAG).	Task + Process (rubric-aligned writing guidance).	*Intermediate → lower elaborated.*	Engagement (Action) and writing performance (Outcome).	The design *relates to macro–micro features* and examines later stages of the learner pathway.
Khor et al. (2025)	School-developed GenAI chatbot (MyBotBuddy); policy context.	Task support (debugging, code explanation).	*Intermediate* (prompt–response).	Usefulness and ease (Perception); intention (Action proxy).	The study focuses on *motivational entry points*, with macro/micro elements indirectly represented.
Gamlem et al. (2025)	Multiple GenAI tools; explicit attention to ethics and trust.	Task/process (applications in lesson planning).	*Basic* (conceptual awareness).	Familiarity and attitudes (Perception).	The contribution *relates mainly to macro and meso layers*, with emphasis on perception rather than behavioural outcomes.
Otaki et al. (2025)	Open LLMs (ChatGPT, Gemini); GDPR and bias acknowledged.	Task ↔ Process (student vs. educator perspectives).	*Intermediate* (informational dialogue).	Trust and ethical judgement (Perception).	The design *touches on macro and micro aspects* through ethical-affective perceptions, with no action/outcome measures.
Kaliisa et al. (2025)	Varied AI systems (2010–2024 studies).	Mostly task (language/writing tasks).	*Basic–intermediate* (heterogeneous designs).	Performance (Outcome) and perception (Perception).	The meta-analysis provides *contextual macro-level trends*, without intermediate actions in aggregated data.

Note. The alignments presented in this table are indicative rather than exhaustive and are intended to support cross-study comparison through the Ba et al. (2025) framework. Individual studies differ in design, analytical focus, and level of theoretical articulation; consequently, not all framework components are operationalised or measured to the same extent. Readers are encouraged to consult the original articles for detailed accounts of methodological decisions, contextual conditions, analytic nuances, etc.

learning. Several studies attend to learner perceptions or short-term actions, while fewer examined subsequent performance outcomes. Hence, early segments of the learner pathway were more frequently studied than longer developmental processes. At the macro level, ethical considerations and system transparency occasionally appear in varying degrees across studies. These patterns do not reflect gaps within individual studies – which were designed for distinct purposes – but highlight areas of the wider AI-assisted feedback ecosystem that remain less empirically developed. As Part II of this Special Issue progresses, forthcoming papers are expected to broaden this picture, particularly in domains related to self-regulation, autonomy, ethical trust, and the longer-term dynamics of AI-supported feedback, enabling a more comprehensive understanding of how technological, pedagogical, and motivational processes interact in increasingly AI-rich learning environments.

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