Investigating student engagement with personalised generative AI feedback: Effects on creative problem-solving and feedback uptake

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Personalised generative artificial intelligence (GenAI) feedback holds potential for supporting students' creative problem-solving, yet empirical evidence on its effects and underlying mechanisms remains limited. This study addressed these gaps through a within-subjects experiment with 62 Chinese university students, aiming to investigate the effects of personalised GenAI feedback on students' creative problem-solving and feedback uptake in comparison with standard GenAI feedback. To further reveal the mechanisms underpinning these effects, we examined how students' interactions and behavioural uptake of feedback during human–AI collaboration were associated with their creative problem-solving performance. Results showed that personalised GenAI feedback improved the quality and elaboration dimensions of students' solutions, while slightly reducing the amount of ignored feedback compared with the standard GenAI condition. Moreover, higher-level uptake of GenAI feedback, reflected in the amount of applied feedback, positively predicted creative problem-solving performance across conditions, and interaction behaviours such as co-constructing ideas and negotiating inconsistencies with AI were consistently associated with this high-level uptake. This study offers insights for designing GenAI feedback that emphasises personalisation to foster students' creative engagement, underscoring the critical role of students' interactive collaboration with AI-generated feedback in cultivating innovation within GenAI-supported learning environments.

Implications for practice or policy:

- When designing personalised agents, AI developers should integrate complementary feedback mechanisms to enhance both student engagement and creative development.
- Educators should prioritise fostering students' higher-level uptake of GenAI feedback, as this is critical to its effectiveness on creative production.
- Instructional approaches should be designed to cultivate students' interactive engagement with GenAI tools and develop their creative capacities, thereby fostering productive human–AI collaboration.

Keyword: generative artificial intelligence (GenAI), personalised feedback, creativity, feedback uptake, experimental study

Introduction

Creativity is widely regarded as an essential competence in 21st-century education, vital for both individual development and societal advancement (Runco & Jaeger, 2012). One approach to fostering creativity is creative problem-solving (CPS), which engages learners with open-ended, ill-defined tasks (Treffinger et al., 2006). CPS refers to the capacity to generate novel and useful solutions to ill-defined problems (Mumford et al., 2019). Successful CPS thus requires the flexible integration and coordination of cognitive and strategic skills throughout the problem-solving process (Mumford et al., 1991).

Although feedback has long been recognised as a cornerstone of effective learning (Hattie & Timperley, 2007), its implementation in open-ended contexts remains challenging (Kinder et al., 2025). Generative artificial intelligence (GenAI) offers new possibilities by enabling real-time, adaptive feedback in dynamic learning environments. Large language models (LLMs) such as ChatGPT have demonstrated considerable potential to augment human creativity (Lee & Chung, 2024) and improve students' CPS (Urban et al., 2024). However, general-purpose GenAI feedback often lacks personalisation, interactivity and emotional responsiveness (Lo et al., 2024; Skulmowski, 2024), underscoring the need for more adaptive and learner-aware systems.

Personalised GenAI feedback offers a promising approach to address these challenges, leveraging the generative flexibility of LLMs to provide context-aware, adaptive support tailored to learners' evolving needs (Maity & Deroy, 2024). Adaptive learning theory (Rachmad, 2022) provides a useful lens for understanding this personalisation by emphasising support tailored to students' needs, pace and preferences, while human-like conversational features may further support students' trust, motivation and engagement in human–AI collaboration (Mogavi et al., 2024).

While advances in GenAI feedback design can enhance its quality and adaptiveness, its effectiveness largely depends on how learners engage with and act upon it (Schiller et al., 2024). Feedback uptake, which refers to the extent to which students integrate feedback into their revisions, is a significant predictor of learning improvement in collaborative settings (Carless & Boud, 2018; Zhang et al., 2021). Given the parallels between peer dialogue and human–AI interaction (Rezwana & Maher, 2023), students' behavioural uptake may thus constitute a key mechanism through which GenAI feedback influences their creative outcomes.

Despite the promising affordances of personalised GenAI feedback, empirical evidence regarding its actual effectiveness and mechanisms in the context of CPS remains scarce. This study aimed to address these gaps by investigating whether and how personalised GenAI feedback influences students' CPS and behavioural uptake of feedback compared with standard GenAI feedback. To this end, a within-subjects experiment was conducted with 62 Chinese university students, each completing two CPS tasks under one feedback condition. By delving into both process- and outcome-level effects, this study provides a deeper understanding of how personalised GenAI feedback influences behavioural engagement and creative outcomes, providing insights for AI designers and educators in developing feedback systems and pedagogical strategies that foster creative engagement and constructive human–AI collaboration.

Literature review

The potential of personalised GenAI feedback for CPS

CPS provides a pedagogical foundation for engaging students in open-ended tasks resembling real-world challenges (van Hooijdonk et al., 2020). Although feedback is a well-established driver of learning (Hattie & Timperley, 2007), conventional forms often fall short in supporting complex tasks. GenAI introduces new possibilities. When appropriately prompted, LLMs such as ChatGPT can produce real-time, context-sensitive feedback that accommodates diverse learning needs (Kinder et al., 2025). Empirical research has shown that ChatGPT facilitates creative idea generation through conceptual synthesis (Lee & Chung, 2024) and increases students' self-efficacy for task resolution, though this effect is not correlated with CPS performance, suggesting self-efficacy may operate independently of actual performance (Urban et al., 2024).

Despite these potentials, general-purpose GenAI feedback presents several limitations in CPS contexts. First, its generic outputs lack alignment with learners' prior knowledge and task-specific goals, reducing the relevance and perceived usefulness of the feedback (Patchan et al., 2016). Second, its limited interactivity restricts students' agentic engagement, which is essential for effectively processing and applying feedback (Lo et al., 2024; Winstone et al., 2017). Finally, the absence of emotional responsiveness may undermine student motivation during complex problem-solving (Joksimovic et al., 2023).

Given the central role of personal factors in creativity development (Yeh, 2011), personalisation provides an important lens for designing GenAI feedback in CPS. Early personalised systems have shown benefits for creative learning, yet their reliance on static learner profiles limits adaptation to evolving learner responses and cognitive states (Maier & Klotz, 2022). Personalised GenAI feedback may overcome this by leveraging LLMs to provide real-time support responsive to individual needs (Maity & Deroy, 2024).

According to adaptive learning theory, effective personalisation involves tailoring learning support to learners' needs, preferences and progress (Rachmad, 2022). In CPS, this entails adapting support to learners' characteristics and evolving task demands, typically implemented in adaptive learning theory - informed adaptive learning through learner modelling (Woolf, 2010) and adaptive feedback (Bimba et al., 2017). Learner modelling diagnoses learners' knowledge states to guide support; empirical evidence indicates that knowledge level and learning style can inform cognitive feedback adaptation (Alshammari & Qtaish, 2019), while feedback tone may support affective and motivational personalisation and students' feedback engagement (Playfoot et al., 2025). Adaptive feedback further allows adjustments based on learners' performance and task demands (Shute & Zapata-Rivera, 2012). Building on these mechanisms and its generative capabilities, personalised GenAI feedback holds promise for fostering student creativity and facilitating CPS. Nevertheless, empirical evidence regarding its effectiveness in CPS remains scarce, highlighting the need for further investigation.

The role of feedback uptake in GenAI-supported learning

From a learner-centred perspective, understanding how students engage with GenAI feedback is key to enhancing its effectiveness. Feedback uptake captures behavioural engagement with feedback and is typically categorised as ignore, copy or apply, with applying rather than copying regarded as higher-level uptake (Zhang et al., 2021). Extending this line of work to GenAI-supported writing, Zhan and Yan (2025) examined students' responses to ChatGPT feedback and identified three revision operations: copy, adaptation and rejection. They found that students' behavioural engagement often remained superficial when requesting feedback, interacting with ChatGPT and revising drafts.

This superficial engagement may be partly attributable to the characteristics of feedback itself. From an adaptive learning theory perspective, feedback is more likely to promote learners' uptake when adapted to their current states and task-specific needs (Shute & Zapata-Rivera, 2012). Supporting this view, Weidlich et al. (2025) found that students perceived automated personalised feedback as more helpful when it was highly informative and process-oriented rather than limited to basic task-completion information. This matters because perceived usefulness shapes how students act on feedback and, consequently, the learning gains they achieve (Winstone et al., 2021). Collectively, these findings suggest that in GenAI-supported contexts, the characteristics of feedback influence behavioural uptake and, ultimately, the learning outcomes of GenAI-based interventions.

The role of interaction in GenAI-assisted creativity

Interaction is a core driver of creativity in collaborative learning. The cognitive–social–motivational model of group creativity posits that creative outcomes arise through iterative cycles of idea stimulation, negotiation and engagement (Paulus & Brown, 2007). Empirical research has demonstrated that dialogic interaction mediates the translation of feedback into learning gains (Zhang et al., 2024). In online peer assessment, students' engagement with peer feedback shaped their uptake behaviours, which subsequently influenced the degree of creative improvement (Zhang et al., 2021). Extending this logic to GenAI-supported contexts, conversational exchanges with LLMs may function as digital analogues to peer dialogue, supporting idea co-construction through iterative feedback loops (Rezwana & Maher, 2023). Thus, students' interactions with GenAI feedback may serve as a mechanism linking feedback uptake to CPS performance.

Studies on GenAI-assisted creativity have primarily emphasised outcome-based assessments (Habib et al., 2024; Urban et al., 2024), while less is known about the behavioural mechanisms underlying these effects. This leaves a gap in understanding how learners engage with AI-generated feedback during co-creation. A deeper investigation into students' dynamic behavioural sequences is essential for unpacking how different types of GenAI feedback influence feedback uptake and, in turn, CPS performance. These insights form the foundation of the present study, which examined how students interact with personalised and standard GenAI feedback in CPS tasks.

The present study

To address these gaps, this study sought to examine how personalised and standard GenAI feedback relate to students' CPS performance, feedback uptake and behavioural sequences during CPS. A within-subjects laboratory experiment was conducted in which participants completed two CPS tasks, each supported in sequence by one of the two GenAI tools. Beyond comparing final outcomes, the study also explored how students' interactions with AI influenced feedback uptake and were associated with variations in CPS performance. Accordingly, the following research questions (RQs) were addressed:

1. Does personalised GenAI feedback affect CPS performance and feedback uptake compared with standard GenAI feedback?
2. What is the relationship between CPS performance and uptake of GenAI feedback under the two GenAI feedback conditions?
3. What behavioural sequences emerge during interactions with different types of GenAI feedback?

Method

Participants

A total of 62 Chinese university students (41 female) from a normal university participated in the study. All experimental instructions and task materials were presented in Chinese, and all interactions between the students and the GenAI systems took place in Chinese. A priori power analyses indicated that a minimum of N = 16 for t tests, N = 67 for exact tests and N = 43 for F tests would be required to detect a medium effect size with a statistical power of $\beta = 0.80$ and $\alpha = 0.05$ (Cohen, 2013). Hence, the final sample size of 62 participants provided adequate statistical power for the primary analyses, though correlational results should be interpreted with caution due to slightly reduced power. Participants represented diverse academic majors and educational levels, with ages ranging from 18 to 27 years ($M = 22.58$, $SD = 2.53$). All but one participant reported prior experience with GenAI tools, and most were more familiar with ChatGPT than with Mr. Ranedeer. Each participant provided informed consent before the experiment and received compensation upon completion. The study was approved by the Ethics Committee of Zhejiang Normal University (approval ID: ZSRT2024306).

GenAI feedback conditions

This study employed two GenAI feedback systems: ChatGPT-4 for the standard condition and Mr. Ranedeer for the personalised condition. While both are based on GPT-4 architecture, they differ fundamentally in interaction design and personalisation. The standard GenAI condition utilised ChatGPT-4 to generate open-ended responses to general prompts, facilitating unstructured exploration. In contrast, the personalised GenAI condition used Mr. Ranedeer, an open-source personalised AI tutor available on the OpenAI platform (https://chat.openai.com/g/g-9PKhaweyb-mr-ranedeer; https://github.com/JushBJJ/Mr.-Ranedeer-AI-Tutor), which tailors feedback by integrating real-time learner input with pre-defined learning preferences. As illustrated in Figure 1, the core distinction between the two conditions lies in interaction workflows.

The personalised GenAI condition was grounded in adaptive learning theory (Shute & Zapata-Rivera, 2012; Woolf, 2010) and operationalised through two interconnected phases.

Phase 1: Learner modelling and instructional planning

Students configured preference-related settings (e.g., knowledge level, learning style and tone style) to establish an initial learner model. Consistent with the adaptive learning principle of individualised instructional planning in intelligent tutoring systems (Woolf, 2010), these settings were then used to generate a personalised learning plan and regulate subsequent AI feedback. For instance, the knowledge level calibrated feedback depth and complexity, the learning style shaped information presentation and the tone style adjusted the affective and motivational framing of feedback. In this way, personalisation was operationalised as a CPS-oriented feedback process that aligned GenAI responses with learner profiles and task demands. Details of the settings are presented in Table A1 in the Appendix.

Phase 2: Dynamic adaptation and scaffolding

Using configuration-based prompting rules and structured response formats, Mr. Ranedeer generated feedback aligned with students' configured preferences and ongoing task input. This phase incorporated strategies such as heuristic questioning and goal-aligned calibration, reflecting the principle of dynamic scaffolding in adaptive educational systems (Shute & Zapata-Rivera, 2012). English translations of representative prompts and GenAI feedback examples from the personalised condition are provided in Table A2 in the Appendix.

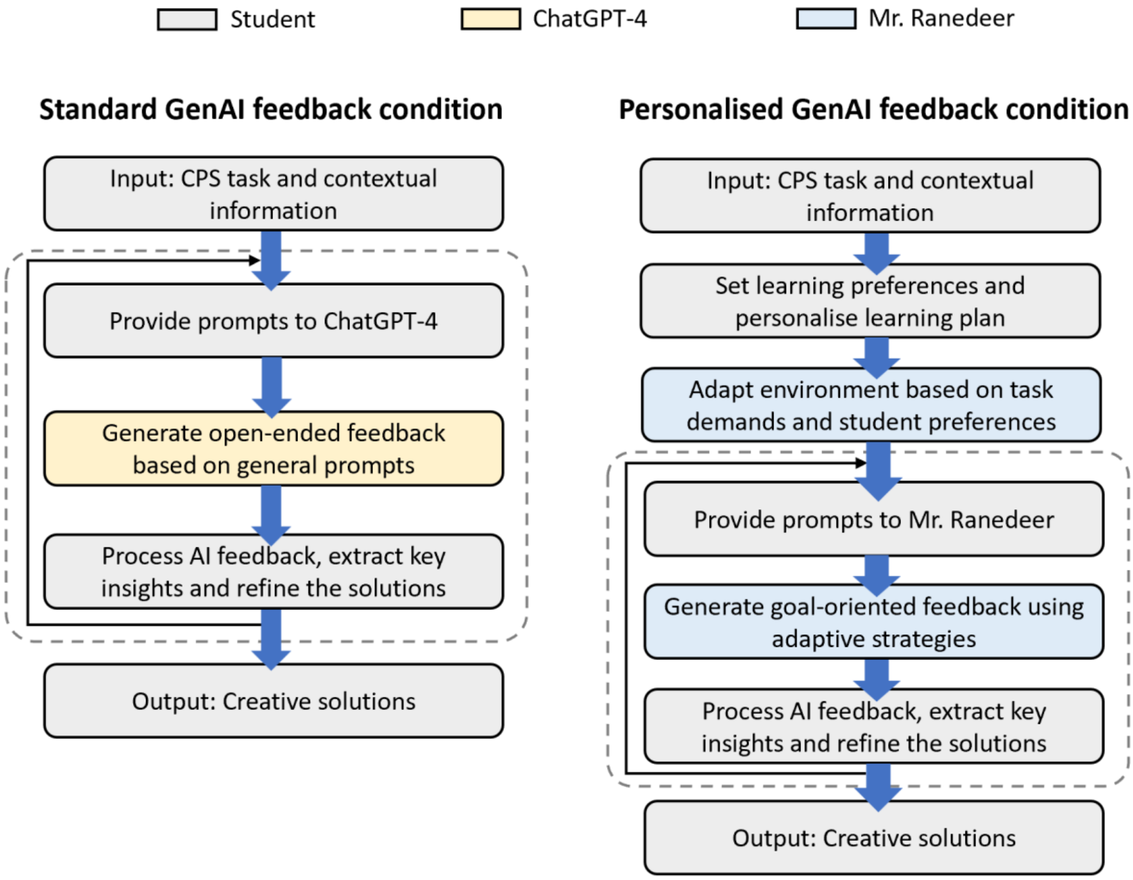

Figure 1. Workflows of two GenAI feedback conditions

Note. Standard condition (left) used a linear process with ChatGPT-4; personalised condition (right) employed a two-phase process consisting of (a) learner modelling and instructional planning and (b) dynamic adaptation and scaffolding via Mr. Ranedeer.

Together, the two phases frame personalisation as a continuous and theory-guided interaction process rather than a one-time configuration, distinguishing it from the standard GenAI condition.

As shown in Figure 2, screenshots of the chat interfaces during the product improvement task (Torrance, 2008), in which a portable coffee maker served as the target product, illustrate the implementation of the workflow distinctions outlined in Figure 1. At task initiation, identical prompts elicited general suggestions from the standard GenAI condition, but triggered a tailored learning plan in the personalised condition. During task execution, when given the same "mood-sensing coffee maker" proposal, the standard GenAI responded with additional features, whereas the personalised GenAI leveraged the learner profile to provide scaffolding (e.g., heuristic questioning) to facilitate conceptual refinement and critical reflection.

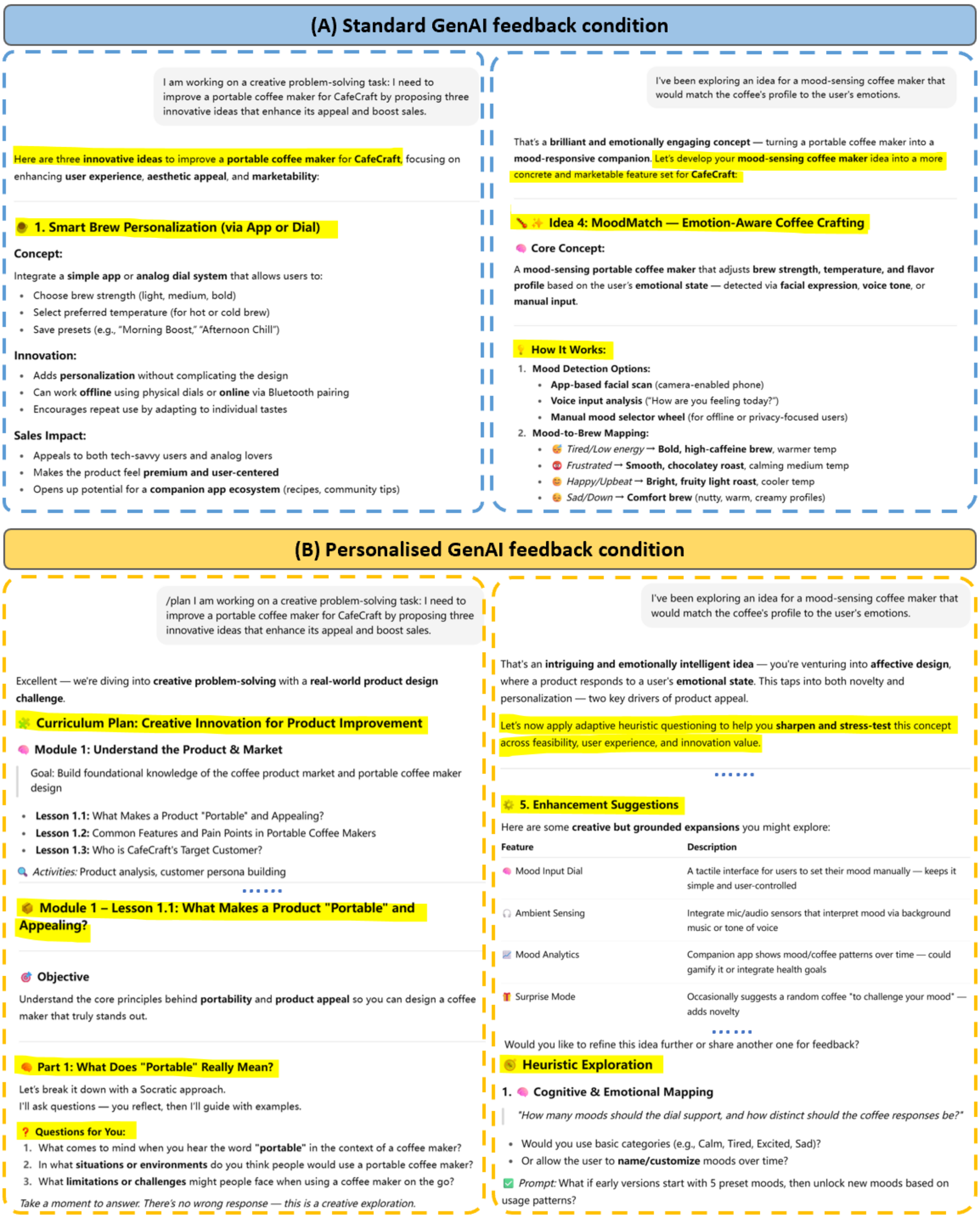

Figure 2. Chat interfaces of two GenAI feedback conditions using identical prompts for task initiation and execution

Note. (A) Standard condition provides general suggestions. (B) Personalised condition provides tailored planning and scaffolding

Measures

CPS performance

The product improvement task (Torrance, 2008) was used to assess CPS performance. Participants were asked to propose three original and useful improvement solutions for two everyday products – a stuffed bunny and a portable coffee maker – using the assigned GenAI tool (ChatGPT-4 or Mr. Ranedeer). To align with real-world creativity research paradigms, students could freely enter prompts and adjust the interaction flow, allowing flexible engagement with GenAI-generated feedback.

In ill-defined tasks, CPS outcomes can be reflected in the solutions produced (Mumford et al., 1991). Accordingly, students' solutions were evaluated on three dimensions – quality, elaboration and originality – following Urban et al. (2024). Quality refers to how well the solutions addressed the task objectives, elaboration captures the level of detail provided and originality reflected novelty. Two trained raters, blinded to the experimental conditions, independently rated all solutions using a 5-point Likert scale (1 = *worst*, 5 = *best*). To control for potential order effects, solutions were presented in a randomised order. Inter-rater reliability was high across all dimensions (Cronbach's kappa = 0.88, 0.90 and 0.86, respectively). Final scores were averaged across the two raters.

Self-efficacy

Self-efficacy was measured using a scale adapted from Urban et al. (2024) and administered before each task to capture condition-specific confidence. Participants rated four items on a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*) assessing their perceived ability to generate original and useful ideas with the assigned GenAI tool. For example, "With the help of [the assigned GenAI], I am confident that I can come up with three original and useful ideas to improve the product", with [the assigned GenAI] replaced by ChatGPT-4 or Mr. Ranedeer. Internal consistency was high across both versions (Cronbach's α = 0.89 and 0.88, respectively).

Procedure

This experiment was conducted individually in a quiet laboratory using desktop computers. Participants first provided demographic information and informed consent, then received instructions on the experimental procedure and on using ChatGPT-4 and Mr. Ranedeer, including a brief introduction to both GenAI models, example prompts and sample responses. A counterbalanced design was implemented: half of the participants (N = 31) completed PIT 1 (stuffed bunny) with ChatGPT-4 and PIT 2 (portable coffee maker) with Mr. Ranedeer, whereas the other half completed the tasks in the reverse order. In both conditions, participants interacted with the assigned GenAI model via the web-based OpenAI interface. They were instructed to treat the tasks as open-ended assignments and submit final responses in Microsoft Word format. A 5-minute break was given between tasks. Mean task completion time was 17 minutes (SD = 7) in the standard condition and 20 minutes (SD = 6) in the personalised condition. The procedure is shown in Figure 3.

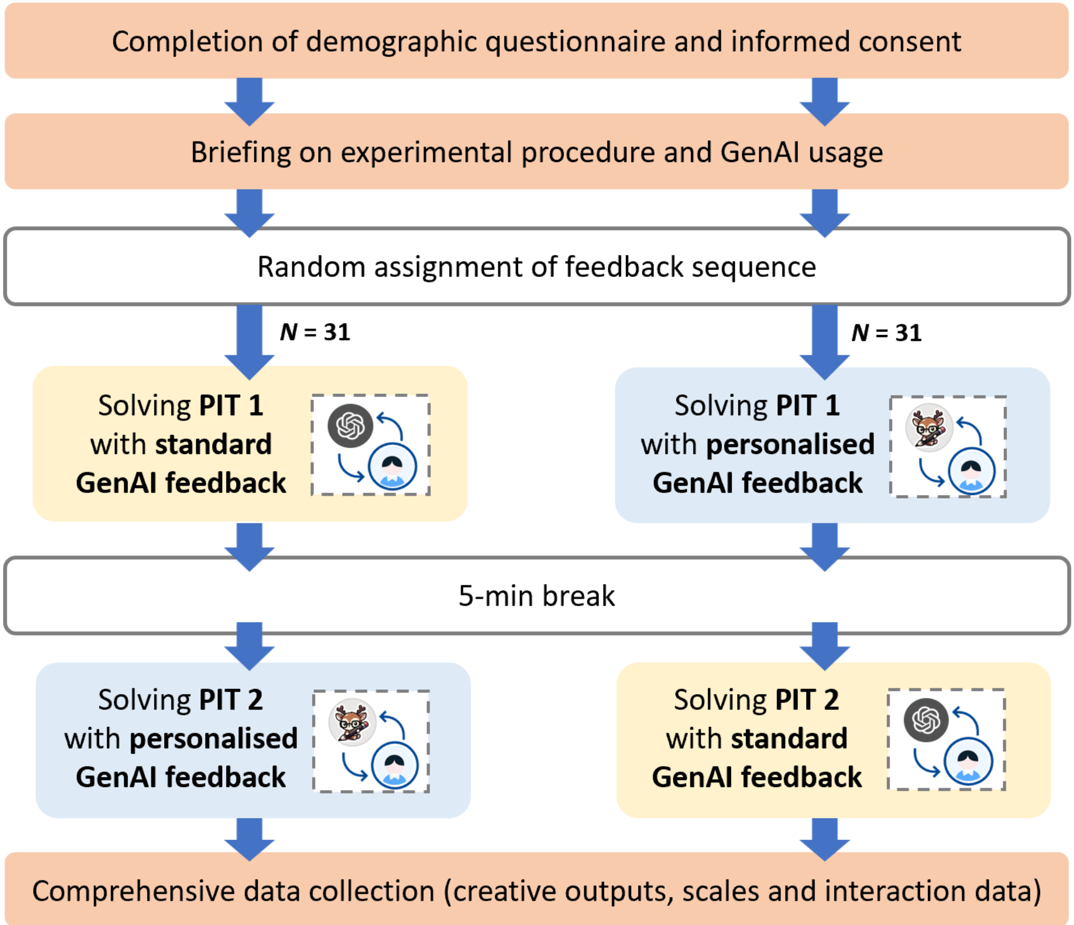

Figure 3. The experimental procedure

Coding scheme

Feedback uptake

Participants' screen activities and conversation logs during the tasks were recorded using screen capture. To assess behavioural engagement with GenAI feedback, uptake behaviour during task revision was coded into three levels – ignore, copy and apply – following Zhang et al. (2021) and Zhang et al. (2024). The "ignore" code indicated that students did not adopt any AI-generated content. "Copy" described the direct insertion of GenAI feedback into their own products without further interpretation or modification. "Apply" captured instances where students critically evaluated GenAI suggestions and expanded upon them using their own creative thinking or elaborations. Each student response following a single AI feedback message served as the coding unit and was assigned to one mutually exclusive uptake level. The frequency of each category was calculated to reflect uptake at each level.

Interaction behaviours

Interaction behaviours were coded in Chinese from the original conversation logs using a scheme adapted from prior research. We translated into the resulting coding scheme into English for presentation in Table 1. The core categories for creative task behaviours were derived from the framework of idea source dynamics (Paulus & Brown, 2007), capturing independent ideation elaboration on AI-generated ideas, and interactive co-construction. Task-relevant interactions incorporated GenAI-specific behaviours (such as planning for personalised learning) by adapting the comprehensive framework of Zhang et al. (2023) for human–AI collaboration. The unit of analysis was each complete student response to AI feedback. Consecutive messages representing a single coherent idea were combined into one unit. The final coding scheme comprised three categories: creative task behaviours, task-relevant interactions and irrelevant content (see Table 1).

Table 1
Coding scheme for students' interaction behaviours in human–AI co-creation

Behaviour	Code	Description	Example
Generate new ideas without interaction	CT1	Provide new solutions without interacting with GenAI	Focusing on users' moods can improve personalised coffee experience.
Build upon GenAI's idea	CT2	Integrate, combine or elaborate on GenAI ideas	Integrating AI into the feedback system could further enhance machine intelligence.
Develop new ideas through interaction	CT3	Propose innovative solutions through inquiry and discussion with GenAI	Can partnering with a well-known brand enhance product visibility?
Plan for personalised learning	TI1	Develop an individualised plan and tailor learning preferences	Suppose you are an experienced product design tutor. Please develop a learning plan to help me solve this task.
Coordinate task or provide substantive information	TI2	Discuss task execution, strategies or background information	My task is to boost the sales of a regular coffee maker. Give me three innovative solutions to achieve this.
Request clarification or solution	TI3	Request clarification or elaboration	What is the difference between a portable coffee maker and regular coffee maker?
Negotiate inconsistencies	TI4	Resolve inconsistencies and refine solutions	The cost is too high; improvements should be more practical and convenient.
Task-irrelevant discourse	I	Discourse unrelated to the assigned task	How can dietary abnormalities be detected using cancer research data?

Note. CT = creative task behaviours. TI = task-relevant interactions. I = irrelevant content.

To validate the coding scheme for feedback uptake and interaction behaviours, two trained raters independently verified its feasibility. They collaboratively coded the data from the first five participants, identifying 43 and 51 behaviours, respectively. Inter-rater reliability was calculated using Cohen's kappa, yielding values of 0.777 and 0.810. After resolving discrepancies through discussion, each rater independently coded half of the remaining data.

Data analysis

First, Wilcoxon signed-rank tests were used to compare CPS performance and feedback uptake between conditions, as Shapiro-Wilk tests indicated non-normality ($p < .05$). Next, correlational analysis and backward regression were conducted to explore the relationship between feedback uptake and CPS performance. The initial regression model included three uptake indicators as predictors and two covariates: prior experience with GenAI and self-efficacy. These covariates were included to control for potential individual differences, with self-efficacy selected based on its established relevance to GenAI-assisted CPS (Urban et al., 2024) and feedback uptake (K. Li et al., 2025). Backward regression was used to mitigate multicollinearity and identify salient predictors. Finally, lag sequential analysis was performed using GSEQ 5.1 to investigate behavioural sequences across GenAI feedback types. Coded behaviour sequences were imported into GSEQ to calculate transition frequencies and adjusted residuals (z score). Statistically significant behavioural transitions from interaction behaviours to feedback uptake were identified using a z score threshold of 1.96, indicating statistically meaningful sequential associations.

Results

Differences in CPS performance and feedback uptake

To address RQ1 regarding the effects of personalised GenAI on CPS performance, Wilcoxon signed-rank tests were performed on performance scores. As shown in Table 2, students obtained significantly higher scores in the personalised GenAI feedback condition in terms of quality (p = .001, r = -0.41) and elaboration (p < .001, r = -0.79). For originality, no statistically significant difference was found between conditions (p = 0.098, r = -0.21). These results suggest that personalised GenAI supported students in generating higher-quality and more elaborate solutions.

Table 2
Descriptive statistics and Wilcoxon signed-rank test results of CPS performance

CPS performance	Standard mean (*SD*)	Personalised mean (*SD*)	*z*	*p*	Cohen's *r*	95% CI for Cohen's *r*
Quality	3.08 (1.12)	3.50 (1.00)	-3.24	.001**	-0.41	[-0.607, -0.166]
Elaboration	2.48 (1.04)	3.58 (1.17)	-6.25	< .001***	-0.79	[-0.885, -0.652]
Originality	3.13 (1.27)	2.92 (1.15)	-1.65	0.098	-0.21	[-0.450, 0.044]

Note. Cohen's r was reported as a measure of effect size, with r = 0.1, r = 0.3, and r = 0.5 corresponding to small, medium and large effects, respectively (Cohen, 2013). The 95% confidence intervals (CI) for Cohen's r are provided in brackets.
*p < .05. **p < .01. ***p < .001.

Additionally, the amount of three feedback uptake levels in each condition was calculated and analysed using Wilcoxon signed-rank tests. As shown in Table 3, a significant difference was found in the amount of ignored feedback (p = 0.036, r = -0.27), suggesting that students were less likely to disregard feedback in the personalised GenAI condition compared to the standard GenAI condition.

Table 3
Descriptive statistics and Wilcoxon signed-rank test results of feedback uptake

Feedback uptake	Standard mean (*SD*)	Personalised mean (*SD*)	*z*	*p*	Cohen's *r*	95% CI for Cohen's *r*
Amount-ignore	2.02 (1.42)	1.58 (1.02)	-2.10	0.036*	-0.27	[-0.497, -0.014]
Amount-copy	1.89 (1.16)	2.24 (1.59)	-1.43	0.152	-0.18	[-0.424, 0.071]
Amount-apply	1.37 (1.66)	1.65 (1.56)	-0.88	0.378	-0.11	[-0.359, 0.144]
Amount-total	5.27 (2.25)	5.47 (2.76)	-0.17	0.862	-0.02	[-0.270, 0.233]

The relationship between feedback uptake and CPS performance

To address RQ2, we first examined the relationships between feedback uptake and CPS performance using correlation analysis, followed by backward regression to identify key predictors of creativity under each condition.

As shown in Table 4, the correlation analyses revealed significant associations between different levels of feedback uptake and CPS performance under both conditions. A consistent pattern emerged, with the amount of applied feedback positively correlated with all three dimensions of student creativity in both the standard (r = .599 to .811, p < .01) and the personalised GenAI conditions (r = .542 to .670, p < .01). However, notable differences emerged between the two conditions. In the standard GenAI condition, no other uptake behaviours showed significant correlations with creativity. By contrast, in the personalised GenAI condition, the amount of ignored feedback was negatively associated with all dimensions of creativity (r = -.369 to -.330, p < .01), while the amount of copied feedback was positively associated with elaboration (r = .561, p < .01) and originality (r = .272, p < .05).

Table 4
Correlations between feedback uptake and CPS performance

Feedback uptake	Standard			Personalised		
	Quality	Elaboration	Originality	Quality	Elaboration	Originality
Amount-ignore	-0.207	-0.095	-0.175	-0.369**	-0.330**	-0.352**
Amount-copy	-0.119	0.155	-0.180	0.232	0.561**	0.272*
Amount-apply	0.811**	0.599**	0.650**	0.670**	0.620**	0.542**

Table 5 presents the final models for each dimension of CPS performance under both conditions, selected through backward elimination. All models reached statistical significance, and the adjusted R^2 values indicated that the retained predictors accounted for a substantial proportion of variance in CPS performance.

Table 5
Model summary of regression models

Model	R	R^2	Adjusted R^2	SEE	ΔR^2	ΔF	$df1$	$df2$	Sig. ΔF
				Standard					
Quality	0.811	0.658	0.652	0.661	-0.006	1.069	1	59	0.305
Elaboration	0.643	0.414	0.394	0.807	-0.015	1.492	1	58	0.227
Originality	0.650	0.422	0.412	0.966	-0.009	0.958	1	59	0.332
				Personalised					
Quality	0.712	0.507	0.491	0.717	-0.007	0.838	1	58	0.364
Elaboration	0.748	0.559	0.528	0.802	-0.001	0.081	1	56	0.777
Originality	0.596	0.356	0.334	0.938	-0.017	1.605	1	58	0.210

Table 6 reports only the focal feedback uptake predictors; retained covariates are not shown. The amount of applied feedback positively predicted all dimensions of CPS performance in both conditions: quality (standard: $\beta = 0.811$, $p < .001$; personalised: $\beta = 0.622$, $p < .001$), elaboration (standard: $\beta = 0.630$, $p < .001$; personalised: $\beta = 0.385$, $p < .001$), and originality (standard: $\beta = 0.650$, $p < .001$; personalised: $\beta = 0.491$, $p < .001$). Additionally, the amount of copied feedback was a positive predictor of elaboration in both conditions (standard: $\beta = 0.238$, $p = 0.021$; personalised: $\beta = 0.377$, $p < .001$). However, key differences emerged in the personalised condition, where the amount of ignored feedback was a negative predictor of the three dimensions of final CPS performance: quality ($\beta = -0.246$, $p = 0.011$), elaboration ($\beta = -0.253$, $p = 0.007$) and originality ($\beta = -0.254$, $p = 0.020$). All final models exhibited low variance inflation factor values (below 1.37), indicating that overfitting concerns were effectively mitigated despite the moderate sample size.

Table 6
Coefficients for feedback uptake predictors of regression models

Model	Predictor	β	t	p	95% CI for B	VIF
			Standard			
Quality	Amount-apply	0.811	10.744	< .001	[0.445, 0.649]	1.000
Elaboration	Amount-apply	0.630	6.263	< .001	[0.267, 0.518]	1.017
	Amount-copy	0.238	2.363	0.021	[0.033, 0.392]	1.017
Originality	Amount-apply	0.650	6.619	< .001	[0.344, 0.642]	1.000
			Personalised			
Quality	Amount-apply	0.622	6.666	< .001	[0.280, 0.521]	1.041
	Amount-ignore	-0.246	-2.635	0.011	[-0.427, -0.058]	1.041
Elaboration	Amount-apply	0.385	3.747	< .001	[0.134, 0.442]	1.009
	Amount-copy	0.377	3.736	< .001	[0.129, 0.426]	1.365
	Amount-ignore	-0.253	-2.804	0.007	[-0.498, -0.083]	1.313
Originality	Amount-apply	0.491	4.608	< .001	[0.205, 0.520]	1.041
	Amount-ignore	-0.254	-2.384	0.020	[-0.528, -0.046]	1.041

Note. β = standardised regression coefficient; B = unstandardised regression coefficient; VIF = variance inflation factor.

The relationship between behavioural sequence and feedback uptake

To address RQ3, we analysed the coded interaction data (see Table 7) and visualised behavioural transitions across three levels of feedback uptake using state diagrams (see Figure 4). A total of 11 statistically significant transitions were identified in the standard condition and 12 in the personalised condition. Shared sequences were marked in blue and condition-specific sequences in orange. Overall, students engaged in more interactions in the personalised condition, with 422 interactions recorded compared with 367 in the standard condition. However, creativity-oriented behaviours (i.e., CT1, CT2 and CT3) were more frequently observed in the standard condition, while task-relevant interactions (i.e., TI1 and TI4) occurred more often in the personalised condition. These patterns suggest that standard GenAI feedback was more closely associated with creativity-oriented engagement, whereas personalised GenAI feedback appeared to foster greater task-oriented engagement.

Table 7
Frequencies of coded interaction behaviours in two GenAI feedback conditions

Condition	CT1	CT2	CT3	TI1	TI2	TI3	TI4	I	Total
Standard	19	34	22	11	163	37	79	2	367
Personalised	9	11	15	118	163	10	91	5	422

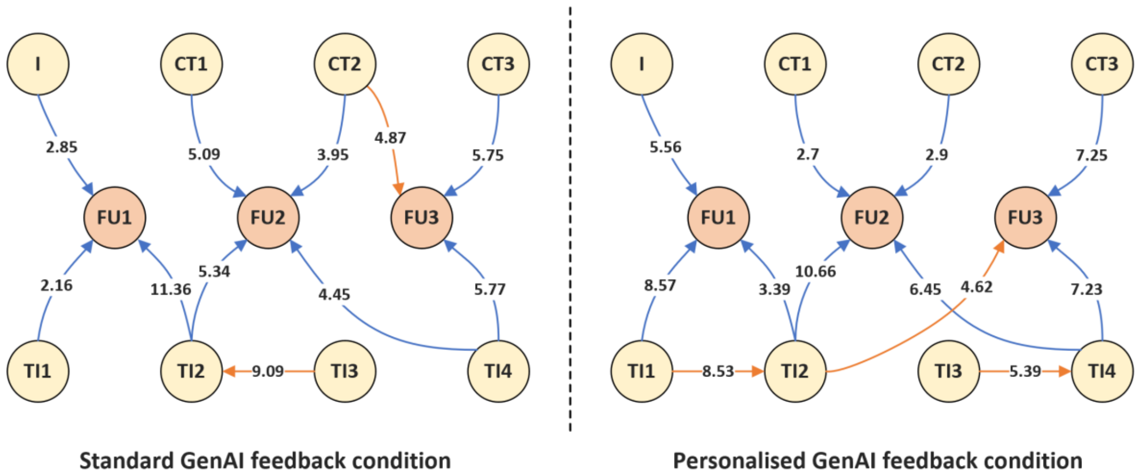

Figure 4. Behavioural transition diagrams of three uptake levels in two conditions
Note. Blue and orange lines indicate similarities and differences in behavioural sequences between conditions.

Several behavioural sequences were consistently associated with feedback uptake across both conditions. Specifically, sequences involving creative ideas generated through GenAI interaction were linked to higher levels of feedback uptake, as reflected by CT1 → FU2, CT2 → FU2, and CT3 → FU3. Similarly, task-relevant interactions, including TI1 → FU1, TI2 → FU1/FU2, TI4 → FU2/FU3, and I → FU1, were observed in both conditions. These findings suggest that both idea generation through interaction (CT3) and negotiation of inconsistencies (TI4) may have facilitated deeper feedback uptake. Condition-specific differences were also noted. CT2 → FU3 and TI3 → TI2 occurred only in the standard condition, while TI1 → TI2 → FU3 and TI3 → TI4 were unique to the personalised condition.

Discussion

This study investigated the effects and mechanisms of personalised versus standard GenAI feedback on students' CPS. It examined whether personalised GenAI feedback influenced students' CPS and feedback uptake and analysed how students' AI interactions and behavioural uptake related to creative outcomes. Using a within-subjects experiment with multimodal data, we combined statistical and lag sequential analyses to capture students' interaction dynamics in GenAI-assisted creativity.

Findings on RQ1

In response to RQ1, personalised GenAI feedback demonstrated a nuanced effect on CPS performance. Compared with standard GenAI feedback, it improved the elaboration and quality of student solutions, though these benefits were limited to specific creative aspects. This partial efficacy aligns with Hattie and Timperley's (2007) model of effective feedback, which underscores the importance of context-sensitive support. Mr. Ranedeer enacted this approach through goal setting ("Feed Up"), performance evaluation ("Feed Back") and actionable guidance ("Feed Forward"). By aligning feedback with task structure, personalised GenAI may have helped students clarify problem boundaries and explore solution paths more systematically. Its pedagogical scaffolds might have further promoted iterative refinement, producing more detailed and focused outputs. However, originality scores did not significantly improve in the personalised GenAI condition. According to self-determination theory (Ryan & Deci, 2000), creativity depends on a balance between autonomous and controlled motivation. General-purpose GenAI tends to support idea generation through exploratory autonomy (Habib et al., 2024), whereas the goal-oriented design of personalised GenAI may introduce a form of controlled motivation that limits divergent thinking. Consequently, although personalisation enhanced certain aspects of CPS performance, it might also inadvertently constrain exploratory freedom essential for original idea generation.

Regarding feedback uptake, personalised GenAI feedback resulted in a slight reduction in the amount of ignored feedback compared to the standard GenAI condition. This small effect may be partly explained by the anthropomorphic and interactive design of the AI tutor, which has been shown to enhance perceived credibility and acceptance of feedback (Skulmowski, 2024). Therefore, the tailored and context-aware nature of personalised feedback appears to have encouraged more consistent behavioural engagement throughout the task. Studies have shown that students are more likely to uptake feedback when it is specific, constructive and aligned with their current learning needs (Wu & Schunn, 2020).

Findings on RQ2

For RQ2, a consistent pattern emerged across both conditions: higher-level uptake (i.e., the amount of applied feedback) was positively correlated with all dimensions of CPS performance and served as the strongest predictor in the regression models. This finding aligns with Zhang et al. (2021), who found that in online peer assessment, the amount of applied self-feedback positively predicted improvements in the creativity of students' artifacts. Extending this to GenAI-supported learning environments, our findings suggest that actively incorporating AI feedback enables students to reorganise and elaborate on their ideas, transforming external input into more coherent and well-structured concepts.

Interestingly, the amount of copied feedback was positively associated with the elaboration of students' solutions across conditions, suggesting that when interacting with GenAI, this form of uptake may facilitate the iterative development of creative ideas. Contrary to traditional views that regard copying as a superficial form of engagement (Zhang et al., 2021; Zhang et al., 2024), this finding indicates that selective imitation can serve as an adaptive strategy in GenAI-mediated learning environments. This interpretation is consistent with Kinder et al. (2025), who found that adaptive LLM-generated feedback promotes more elaborate reasoning when aligned with learners' goals and task demands.

Beyond this shared pattern, a small yet consistent negative effect was observed for ignored feedback in the personalised GenAI condition, suggesting that disengagement may constrain the potential benefits of personalisation. This finding aligns with evidence that interactive, dialogic AI tools enhance students' utilisation and perception of feedback (Mogavi et al., 2024), highlighting the importance of sustained engagement for the effective use of adaptive feedback.

Findings on RQ3

With respect to RQ3, the sequential analysis revealed converging interaction behaviours that relate to high-level uptake across both conditions: idea generation through interaction (CT3) and negotiating conceptual inconsistencies (TI4). These patterns indicate that students were more likely to integrate AI feedback meaningfully when they engaged in iterative co-construction or actively resolved cognitive discrepancies with AI. This observation aligns with collaborative learning research showing that reciprocal information exchange and cognitive conflict resolution are critical to deeper engagement and knowledge elaboration (Benvenuti & Mazzoni, 2020; Paulus & Brown, 2007). These findings underscore that productive human–AI co-creation hinges not only on feedback characteristics but also on dialogic interaction patterns that enable mutual construction.

Moreover, distinct interaction dynamics emerged during the creative initiation. Under the standard GenAI condition, the TI3 → TI2 sequence reflected reactive information-seeking. This aligns with recent studies identifying cognitive offloading as a prevalent tendency in student–ChatGPT interactions, wherein learners' engagement appeared superficial rather than actively constructing their own understanding (S. Li et al., 2025; Zhan & Yan, 2025). In contrast, the more frequent TI1 → TI2 transition in the personalised GenAI condition suggests that students were more likely to proactively provide contextual information at the outset, thereby guiding the trajectory of AI-generated feedback. These contrasting patterns suggest that system design may influence how learners initiate and coordinate feedback dialogues, with standard GenAI prompting more reactive queries and personalised GenAI fostering more context-aware and goal-directed exchanges. Taken together, these exploratory findings suggest that even subtle design variations in GenAI tools may affect the flow of student–AI interaction, despite sharing similar functional goals in GenAI-supported learning.

Limitations and future directions

The current study has several limitations that should be addressed in future research. First, although this within-subjects, one-shot design was suitable for examining task-specific CPS performance and feedback uptake under controlled conditions, the ecological validity of our findings may be constrained by the decontextualised nature of the laboratory setting and the use of the pre-defined task, which limited the assessment to short-term CPS performance under each GenAI feedback condition. Moreover, the relatively small sample (N = 62) drawn from a Chinese university may restrict the generalisability of the results to other educational and cultural contexts. To address these limitations, future research should replicate these findings with larger, more diverse and cross-cultural samples in authentic classroom environments, where non-verbal cues (e.g., facial expressions, gestures) could provide richer insights into the dynamics of student–AI interaction (Güner & Er, 2025); investigate different types of GenAI feedback across a broader range of learning activities, such as collaborative learning environments, as task characteristics and social context in such complex settings may fundamentally influence how students collaborate with AI (Kovari, 2025); and employ longitudinal designs with extended interventions to examine whether the effects of personalised GenAI feedback on creativity persist over time.

Second, although this study investigated the cognitive and social aspects of students' interaction with GenAI feedback, it did not take into account individual differences such as creative potential (Treffinger et al., 2008), domain knowledge (Sun et al., 2020) and feedback literacy (Carless & Boud, 2018) – all of which are known to influence students' feedback engagement and creative outcomes in online collaborative settings. In addition, the affective valence reflected in peers' feedback may also affect students' feedback uptake and, in turn, their improvement in creativity (Zhang et al., 2021). Therefore, future research should explore the interplay between individual differences and affective factors in shaping student engagement with AI-generated feedback.

Third, while the findings revealed associations between behavioural engagement with GenAI feedback and creative outcomes, the underlying mechanisms of GenAI-assisted creativity warrant further clarification. Future research could integrate multimodal evidence, such as eye-tracking and think-aloud protocols, which have proven effective in uncovering implicit cognitive processes (Cheng et al., 2024). Additionally, although key confounders such as prior GenAI experience and self-efficacy were controlled when predicting CPS performance, other unmeasured factors may also explain the observed differences, particularly regarding students' engagement preferences and their interpretation of AI feedback (Dann et al., 2024).

Finally, despite its potential to enhance students' creative engagement, personalised GenAI feedback shows limited capacity in fostering original thinking. Future work could explore how personalised AI agents can be architected to integrate pedagogical strategies that simultaneously promote feedback engagement and innovative thinking. For instance, embedding divergent thinking training (Sun et al., 2020) and regulatory scaffolds (Alemdag & Yildirim, 2022) into agent design could enable such systems not only to tailor feedback but also to actively cultivate student creative growth.

Conclusion

In conclusion, this study compared the effects of personalised versus standard GenAI feedback on students' CPS performance and feedback uptake within experimental tasks. The results suggest that personalised GenAI feedback is associated with higher solution quality and elaboration, as well as less ignored feedback, compared to the standard GenAI. Further analyses revealed that students' higher-level uptake of GenAI feedback – closely tied to co-constructing ideas and negotiating inconsistencies with AI – consistently predicts CPS performance across conditions. As an early investigation into personalisation in creative contexts, this study offers initial insights into how GenAI feedback supports student–AI collaboration and provides preliminary evidence on the mechanisms through which AI feedback relates to student creativity under the experimental conditions.

The findings offer practical implications for fostering human–AI co-creativity in educational settings. First, given the distinct affordances of different types of GenAI feedback, AI designers should consider integrating complementary features, including adaptive personalisation, strategic scaffolding and context-aware prompting, to support the multifaceted development of students' creative thinking. Second, since higher-level uptake of GenAI feedback predicted better CPS performance, educators should guide students to critically evaluate and meaningfully apply AI-generated content rather than adopting it superficially. Finally, the observed links between specific interaction behaviours and feedback uptake suggest that instructional approaches should cultivate active engagement strategies. Promoting co-constructive dialogue, iterative experimentation and critical reflection may enhance students' feedback processing and facilitate more productive human–AI collaboration.

Author contributions

Yixuan Chen: Conceptualisation, Writing – original draft, Writing – review and editing; **Changqin Huang:** Investigation, Supervision, Writing – review and editing; **Zhongmei Han:** Writing – review and editing; **Di Zhang:** Data curation, Formal analysis; **Yiheng Lou:** Behavioural coding; **Yihua Zhong:** Data collection.

Funding

This work was supported by the National Natural Science Foundation of China (grant no. 62337001).

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Please cite as: Chen, Y., Huang, C., Han, Z., Zhang, D., Lou, Y., & Zhong, Y. (2026). Investigating student engagement with personalised generative AI feedback: Effects on creative problem-solving and feedback uptake. *Australasian Journal of Educational Technology*, *42*(4), 165–185. https://doi.org/10.14742/ajet.11512

Appendix

Table A1
Personalisation settings in Mr. Ranedeer and their roles in CPS-oriented feedback

Preference setting	Role in personalisation	Roles in CPS-oriented feedback
Knowledge level	Establishes learners' initial knowledge profiles	Calibrates feedback depth and complexity to learners' current understanding
Learning style	Specifies preferred information processing	Shapes how feedback is presented to support understanding and engagement
Tone style	Sets affective and motivational framing	Adjusts warmth, directness and encouragement to support trust and willingness to act on feedback
Communication style	Specifies mode of instructional communication	Influences whether feedback is formal, conversational, concise, detailed, storytelling-based or Socratic
Personalised learning plan	Converts preferences into a task-support pathway	Organises subsequent guidance around problem understanding, idea development and solution refinement

Table A2
Representative prompts and GenAI feedback examples in the personalised condition

Interaction component	Representative prompt	Representative GenAI feedback
Learner configuration	/Config knowledge level, learning style, tone style, communication style.	Configuration updated: Knowledge level: Basic; learning style: active + reflective; tone style: encouraging + informative; communication style: socratic.
Personalised learning plan	/Plan design a portable coffee maker with three innovative ideas to enhance appeal and boost sales.	Custom learning plan: Module 1: Understand the product and market. Objective: Propose three feasible and creative enhancements that improve appeal and boost sales.
Task initiation	I've been exploring an idea for a mood-sensing coffee maker that matches the coffee profile to the user's emotional state.	How could the coffee device adapt to the user's emotional state while balancing personalisation, novelty, and feasibility? Refined concept: Mood-tuned coffee maker – a portable coffee maker that lets users select moods and receive matched coffee suggestions.
Task execution	What if we combine a mood input dial with mood analytics?	Strategic feedback and heuristic exploration: Cognitive and emotional mapping: Decide the number of mood categories and distinct coffee responses; consider basic categories (e.g., calm, tired, excited, sad) or customisable labels. Heuristic exploration: Use users' interaction patterns to refine mood–coffee mapping and test feasibility across scenarios. Enhancement suggestions: Propose feasible creative expansions, such as mood input dial, ambient sensing, mood

Interaction component	Representative prompt	Representative GenAI feedback
		analytics or surprise mode, while balancing novelty and usability. Final heuristic challenge: Clarify the emotional value for users, such as an improved coffee experience, alignment with daily rhythms or playful reflection on mood.