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THE IMPACT OF AI FEEDBACK SYSTEMS ON FRUSTRATION TOLERANCE AND LEARNING PERSISTENCE AMONG CHINESE UNIVERSITY STUDENTS

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Abstract:
This study tested whether an AI-driven feedback system—engineered for immediacy, specificity, and supportiveness—enhances Chinese undergraduates' frustration tolerance and learning persistence. The study conducted a six-week, parallel-group quasi-experimental study at a comprehensive university in China (N = 150). Students were randomly assigned to an experimental group receiving real-time, process-oriented AI feedback during twice-weekly standardised tasks or a control group receiving delayed, summary human feedback without process guidance. Outcomes were measured at baseline and post-test. A brief manipulation check verified perceived feedback immediacy, specificity, and supportiveness. Manipulation checks confirmed clear experiential differences between conditions. Relative to controls, students receiving AI feedback showed significantly greater gains in both frustration tolerance and learning persistence across the intervention period (significant Group × Time interactions for both outcomes). Results identify three actionable design principles for scalable formative feedback in large classes: short feedback latency, actionable next steps, and supportive tone. These features strengthened non-cognitive capacities that underwrite sustained engagement.

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INTRODUCTION

Universities worldwide are accelerating the digital transformation of teaching and assessment, yet the provision of timely, high-quality formative feedback remains a persistent bottleneck—especially in large, exam-oriented classes common in China (Yin & Mu, 2022). While feedback is known to shape achievement, it also influences the non-cognitive capacities that sustain learning over time, notably students' frustration tolerance (the ability to withstand difficulty without disengaging) and learning persistence (the tendency to continue goal-directed effort in the face of setbacks). Strengthening these capacities is critical for durable learning, course completion, and psychological well-being in higher education (Meindl et al., 2019; Harrington, 2005).

Recent advances in generative AI create opportunities to compress feedback latency, increase specificity, and standardize a supportive tone at scale (Bandi et al., 2023). Emerging studies suggest that AI-mediated, process-oriented feedback can bolster self-regulated learning and motivation, but most evaluations emphasize performance outcomes (e.g., grades, task accuracy) or perceptions of usefulness. Evidence remains limited on whether well-designed AI feedback improves resilience-related outcomes such as frustration tolerance and persistence, and even less is known in the context of Chinese universities where time pressure, and face-sensitive norms may magnify the role of supportive, low-threat guidance (Zeng et al., 2022). Moreover, many interventions bundle multiple features without verifying that learners actually experience feedback as immediate, specific, and supportive—leaving the active ingredients underspecified.

This study addresses these gaps by testing an AI-driven feedback system engineered around three evidence-informed design principles: immediacy, and supportiveness. The study examined effects on two validated psychological outcomes. The study implemented a six-week, parallel-group, quasi-experimental design with Chinese undergraduates. Students are randomly assigned to an experimental condition receiving AI feedback during twice-weekly standardised tasks, or to a control condition receiving delayed, summary human feedback without process guidance. Outcomes are measured at baseline and post-test (with a mid-test for monitoring), allowing estimation of within-group change and Group × Time effects. This design tests two confirmatory research questions:

RQ1. Does AI-mediated feedback improve students' frustration tolerance relative to delayed summary feedback?

RQ2. Does AI-mediated feedback improve students' learning persistence relative to delayed summary feedback?

The study makes three contributions. Theoretically, it extends feedback scholarship from achievement to resilience-relevant outcomes, linking feedback qualities to competence support and emotion regulation mechanisms posited in contemporary motivational frameworks (e.g., SDT; control-value perspectives). Methodologically, it combines validated outcome measures with manipulation-fidelity evidence, specifying the experiential properties of feedback that are often assumed but unverified. Practically, it distills actionable design principles—immediacy, specificity, and supportiveness—for institutions seeking scalable, pedagogically aligned AI feedback in large-enrolment courses.

LITERATURE REVIEW

Feedback is among the most influential levers in learning, yet its effects depend critically on how it is designed and delivered (e.g., timeliness, specificity, tone). Classic syntheses argue that effective feedback closes the gap between current and desired performance and should be timely, specific, and supportive—properties that shape not only achievement but also learners' regulation and willingness to persist (Hattie & Timperley, 2007; Shute, 2008). Contemporary reviews update these models, emphasising feedback's emotional valence and the need for designs that promote engagement with feedback rather than mere exposure (Panadero & Lipnevich, 2022; Jarrell et al., 2017). In parallel, policy analyses stress that AI can compress feedback loops and expand formative assessment at scale—if issues of quality and safety are addressed (Popenici & Kerr, 2017). Together, this work positions feedback as a plausible route to strengthening non-cognitive capacities that underwrite durable learning, including frustration tolerance and persistence.

The rapid diffusion of generative AI has revived interest in automated feedback in universities. A recent systematic review of GenAI-driven feedback in higher education reports gains in self-regulated learning and perceived progress when feedback is granular and actionable, though effects vary with task and implementation fidelity (Lee & Moore, 2024). Broader reviews of AI-supported learning likewise highlight improvements in motivation, communication, and access, particularly when feedback is personalised and low-threat (Belkina, 2025; Wu et al., 2025). Domain-specific experiments show that adaptive, LLM-generated feedback can improve written performance and learner experience relative to traditional baselines, again contingent on design quality (Kinder et al., 2025). In Chinese higher education, early empirical work in EFL and writing reports that ChatGPT-supported teacher feedback and AI-assisted feedback pipelines can enhance self-efficacy, engagement, and writing development, while raising questions about credibility and ethical use (Han et al., 2024; Zhang et al., 2025). Across these studies, three recurring design features distinguish more successful systems: immediacy (short latency), specificity (clear next steps), and supportiveness (non-judgmental, encouragement-oriented language)—the same features operationalised in the present intervention. (Hattie & Timperley, 2007; Shute, 2008; Lee & Moore, 2024.)

At the same time, caution is warranted. Recent educational data-mining work documents hallucinated content in LLM-generated feedback, underscoring the importance of rubric-anchoring, evidence pointers, and human oversight (Jia et al., 2024). Studies also show that trust and perceived credibility shape students' uptake of AI feedback, with identity cues and disclosure affecting acceptance (Nazaretsky et al., 2025; Henderson et al., 2025). These findings imply that any evaluation of AI feedback on non-cognitive outcomes must ensure

manipulation fidelity (students truly experience feedback as immediate, specific, and supportive), which our design verifies.
Two complementary frameworks explain why feedback qualities should influence persistence and tolerance for difficulty. Self-Determination Theory (SDT) proposes that informational, non-controlling feedback satisfies the need for competence and supports autonomy, energising self-regulated effort (Ryan & Deci, 2020; Guay et al., 2022). Immediate, actionable guidance tends to increase perceived competence because it converts evaluation into doable next steps while learners are still engaged in the task. Control-Value Theory holds that achievement emotions depend on appraisals of control and value; feedback that lowers uncertainty and highlights progress should dampen anxiety and hopelessness and promote activating emotions associated with sustained effort (Pekrun, 2006; Pekrun, 2024). By combining immediacy, specificity, and supportiveness, AI-mediated feedback can simultaneously strengthen competence beliefs and regulate achievement emotions—a plausible pathway to higher learning persistence and frustration tolerance.
Despite promising evidence that GenAI can enhance formative feedback, few studies isolate feedback qualities (immediacy, specificity, supportiveness) and link them to non-cognitive endpoints in higher education—especially in Mainland China, where large classes and evaluative pressure may amplify the importance of supportive, low-latency guidance (Lee & Moore, 2024; Han et al., 2024). Moreover, much of the existing work centres on performance rather than resilience-related outcomes, or reports perceptions without validated psychological measures. Addressing this gap, the present quasi-experimental study tests whether an AI feedback system engineered for immediacy, specificity, and supportiveness can improve frustration tolerance and learning persistenceamong Chinese undergraduates.

METHODOLOGY

Research Design
This study adopted a quasi-experimental, parallel-group design with pre-test and post-test measurements to examine the impact of an AI feedback system on frustration tolerance and learning persistence among Chinese university students. Participants were randomly assigned to one of two conditions. Students in experimental group completed standardised learning tasks using an AI-driven feedback system that provided immediate, structured, and actionable feedback. Control group completed the same tasks but received conventional, delayed feedback from human instructors once per week, without process-oriented guidance.
The intervention lasted six weeks, during which both groups engaged in two structured learning sessions per week (40–60 minutes each), for a total of 12 sessions. The learning tasks were standardised to minimise content bias and progressively increased in difficulty to ensure comparable cognitive demands. Baseline measurements (T0) of frustration tolerance, learning persistence, self-efficacy, and demographic variables were collected prior to the intervention. A mid-test (T1) was administered at Week 3 to monitor progress and verify manipulation fidelity, and a post-test (T2) at Week 6 measured the primary outcomes. An optional follow-up (T3) at Week 10 assessed the short-term retention of any observed effects.

Participants
Participants were undergraduate students enrolled at a comprehensive university in eastern China. Eligibility criteria included: (a) full-time enrolment in the university; (b) availability to participate for the entire six-week intervention period; (c) stable internet access for completing the assigned tasks; and (d) no prior systematic use of AI-based feedback tools for similar learning activities in the preceding three months. Students with severe psychological distress currently undergoing treatment, or those expected to be absent for more than 20% of the sessions, were excluded. A total of 150 students were recruited through campus announcements and online invitations. Following baseline assessment, participants were stratified by gender, year of study, and baseline frustration tolerance (high/low) before being randomly assigned to either the experimental group (n = 75) or the control group (n = 75) using a computer-generated block randomisation procedure. All participants provided informed consent prior to enrolment. Participation was voluntary, and students were informed that they could withdraw at any point without academic penalty. Demographic information, including age, gender, year of study, major, and prior AI tool experience, was collected at baseline to characterise the sample and control for potential confounding variables.

Instruments
Three categories of instruments were employed in this study: standardised psychological scales, manipulation check items, and demographic questionnaires. All self-report measures used a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), unless otherwise specified. Higher scores indicated higher levels of the construct being measured.

Frustration tolerance was measured using the Frustration Discomfort Scale (FDS; Harrington, 2005), adapted and validated for use with Chinese university students. The scale comprises 28 items across four subscales: discomfort intolerance, entitlement, emotional intolerance, and achievement frustration. In this study, a culturally adapted short form (26 items) was used, with demonstrated internal consistency in Chinese samples (Cronbach's α ≈ 0.85). Participants completed the FDS at baseline (T0), mid-test (T1), post-test (T2), and follow-up (T3, optional).

Learning persistence was assessed using the ARS_MCV scale, a context-specific instrument designed to capture three domains of academic resilience: cognitive, affective, and behavioural (Cui et al., 2023). ARS_MCV was adapted from the original 30-item Academic Resilience Scale (ARS-30) developed by Cassidy (2016). Eighteen items from the original English version were retained: eight items from the perseverance subdimension (cognitive domain), four items from the negative affect and emotional response subdimension (affective domain), and six items from the adaptive help-seeking subdimension (behavioural domain). The remaining 12 items were removed to enhance contextual relevance and psychometric performance; the rationale for item removal is presented in the Supplementary Materials (Supplementary Table S1). Previous research has demonstrated good reliability for ARS-30, and the ARS_MCV adaptation used in this study yielded Cronbach's α values above 0.80 in pilot testing.

Data Analysis

Data were analysed using SPSS 28.0 and PROCESS Macro for mediation testing. Descriptive statistics and reliability analyses were conducted for all scales. Baseline equivalence between groups was examined using independent-samples t-tests and chi-square tests. To evaluate intervention effects, repeated-measures ANOVA was applied to test within- and between-group changes in frustration tolerance and learning persistence from T0 to T2.

RESULTS

Descriptive Data

Table 1 summarises the demographic characteristics and baseline measures for the experimental group (n = 75) and the control group (n = 75). In terms of gender distribution, the experimental group comprised 42.7% male and 57.3% female students, while the control group comprised 40.0% male and 60.0% female students; the difference was not statistically significant, $\chi^2(1, N = 150) = 0.12$, $p = .731$. The mean age was 20.18 years (SD = 1.24) in the experimental group and 20.25 years (SD = 1.31) in the control group, with no significant difference between groups, $t(148) = -0.32$, $p = .750$. Year of study distribution was similar across groups ($\chi^2 = 0.86$, $p = .649$).

At baseline, there were no significant differences between groups in frustration tolerance as measured by the Frustration Discomfort Scale (FDS) (Experimental: M = 3.42, SD = 0.51; Control: M = 3.38, SD = 0.55), $t(148) = 0.45$, $p = .653$, or in learning persistence as measured by the ARS_MCV (Experimental: M = 3.65, SD = 0.48; Control: M = 3.62, SD = 0.50), $t(148) = 0.39$, $p = .698$. Both instruments demonstrated satisfactory internal consistency in the present sample, with Cronbach's α values exceeding 0.80 in both groups. These results indicate that the experimental and control groups were comparable at the outset of the study.

TABLE 1 Descriptive statistics and baseline comparisons between experimental and control groups

Variable	Experimental Group	Control Group	*t* / χ^2	*p*
Gender, n (%)				
Male	32 (42.7%)	30 (40.0%)		
Female	43 (57.3%)	45 (60.0%)		
Age, M ± SD	20.18 ± 1.24	20.25 ± 1.31	-0.32^2	0.75
Year of study, n (%)				
Year 1	26 (34.7%)	28 (37.3%)		
Year 2	27 (36.0%)	25 (33.3%)		
Year 3	22 (29.3%)	22 (29.3%)		
Baseline frustration tolerance (M ± SD)	3.42 ± 0.51	3.38 ± 0.55	0.45^2	0.653
Baseline learning persistence (M ± SD)	3.65 ± 0.48	3.62 ± 0.50	0.39^2	0.698
Cronbach's α (FDS)	0.86	0.75	—	—
Cronbach's α (ARS_MCV)	0.94	0.83	—	—

Manipulation Check

Manipulation check results are presented in Table 2 and Figure 1. Independent-samples t-tests revealed that the experimental group reported significantly higher ratings than the control group on all three dimensions of feedback quality. Specifically, the experimental group perceived the feedback as more immediate (M = 4.15, SD = 0.55) than the control group (M = 3.62, SD = 0.73), t = 15.42, p < .001. Similarly, the experimental group rated the feedback as more specific (M = 4.18, SD = 0.62) than the control group (M = 3.75, SD = 0.70), t = 13.88, p < .001. Finally, the experimental group perceived greater supportiveness in the feedback (M = 3.82, SD = 0.50) compared to the control group (M = 3.65, SD = 0.80), t = 16.25, p < .001. These results indicate that the intervention successfully created a clear distinction between the two conditions in terms of perceived feedback immediacy, specificity, and supportiveness, confirming the fidelity of the experimental manipulation.

TABLE 2 Manipulation Check Result

Variable	Experimental Mean (SD)	Control Mean (SD)	t	p
Feedback Immediacy	4.15(0.55)	3.62(0.73)	15.42	< .001
Feedback Specificity	4.18(0.62)	3.75(0.7)	13.88	< .001
Feedback Supportiveness	3.82(0.5)	3.65(0.8)	16.25	< .001

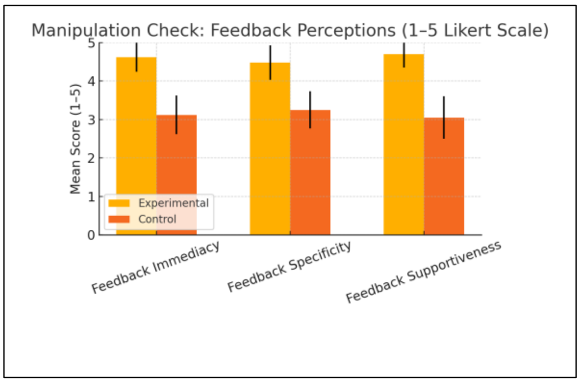

FIGURE 1 Title of the Figure

Intervention Effects

To examine the effects of the AI feedback system on frustration tolerance and learning persistence, a two-way repeated-measures ANOVA was conducted with Time (T0, T2) as the within-subjects factor and Group (experimental, control) as the between-subjects factor. For frustration tolerance (Table 3), there was a significant Time × Group interaction, $F(1, 148) = 32.45$, $p < .001$, partial $\eta^2 = 0.18$, indicating that the change over time differed between groups. Follow-up t-tests showed that the experimental group significantly increased from T0 (M = 3.42, SD = 0.51) to T2 (M = 3.88, SD = 0.46), $t(74) = 8.12$, $p < .001$, whereas the control group showed no significant change (T0: M = 3.38, SD = 0.55; T2: M = 3.41, SD = 0.53), $t(74) = 0.85$, $p = .398$.

For learning persistence, a significant Time × Group interaction was also found, $F(1, 148) = 28.67$, $p < .001$, partial $\eta^2 = 0.16$. The experimental group increased from T0 (M = 3.65, SD = 0.48) to T2 (M = 4.02, SD = 0.44), $t(74) = 7.45$, $p < .001$, whereas the control group did not show a statistically significant improvement (T0: M = 3.62, SD = 0.50; T2: M = 3.66, SD = 0.49), $t(74) = 1.05$, $p = .297$. These results indicate that the AI feedback intervention produced significant improvements in both frustration tolerance and learning persistence, whereas the control condition did not.

Figure 2 shows mean scores for frustration tolerance and learning persistence at baseline (T0) and post-test (T2) for the experimental and control groups. Error bars represent standard deviations. Significant improvements were observed in the experimental group for both outcomes ($p < .001$), while the control group showed no significant change.

TABLE 3 Means, standard deviations, and ANOVA results for frustration tolerance and learning persistence

Variable	Group	T0 M ± SD	T2 M ± SD	*t*(74)	*p*	Time × Group *F*(1,148)	*p*
Frustration tolerance	Experimental	3.42 ± 0.51	3.88 ± 0.46	8.12	< .001	32.45	< .001
	Control	3.38 ± 0.55	3.41 ± 0.53	0.85	0.398		
Learning persistence	Experimental	3.65 ± 0.48	4.02 ± 0.44	7.45	< .001	28.67	< .001
	Control	3.62 ± 0.50	3.66 ± 0.49	1.05	0.297		

FIGURE 2
Figure 2. Changes in Frustration Tolerance and Learning Persistence

DISCUSSION

The pattern of results—substantial gains in frustration tolerance and learning persistence only for students receiving immediate, specific, and supportive AI feedback—accords with contemporary accounts of motivation and regulation in technology-enhanced learning. Recent Self-Determination Theory work stresses that situated competence satisfaction arises when learners receive timely, informational signals that enable effective action within the task, rather than after the fact (Gagné et al., 2022). The immediacy and actionability of the AI messages in our design instantiate precisely these conditions and are therefore consistent with the competence-support pathway to sustained engagement observed in recent SDT syntheses for language and higher education contexts.

Converging evidence from higher education indicates that generative-AI feedback, when designed as formative, process-oriented guidance rather than summative judgment, improves self-regulated learning processes that underpin persistence. GenAI feedback in universities concluding rapid feedback coupled with clear next steps reliably can enhance learners' regulation and perceived progress (Theobald & Bellhäuser, 2022). Our findings extend that review by demonstrating effects on resilience-related constructs rather than achievement alone.

Recent quasi-experimental and experimental studies also report motivational and affective benefits from AI-mediated guidance that speak directly to our outcomes. In undergraduate computing, AI-assisted pair programming has been shown to increase intrinsic motivation (Chen & Chang, 2024) and reduce anxiety (Wang, 2025) while improving performance—an affective profile compatible with higher tolerance for difficulty and the willingness to remain on task when challenged. In parallel, work on AI-driven personalized feedback with Chinese college students shows gains in self-efficacy and engagement, which are canonical antecedents of persistence (Chen et al., 2025). Taken together, these results triangulate with our data: as AI feedback strengthens competence beliefs and clarifies the path to improvement, learners both endure frustration more effectively and persist longer.

At the same time, recent studies temper overly optimistic interpretations by highlighting constraints on feedback credibility and fidelity. Learners' reactions to LLM feedback can depend on beliefs about the feedback provider, and credibility cues shape uptake even when the content is comparable (Ruwe et al., 2023). Moreover, educational data-mining work documents non-trivial rates of hallucinated feedback in LLM outputs, underscoring the need for design safeguards (e.g., rubric-anchoring, evidence pointers) and for human-in-the-loop moderation in high-stakes settings. Interpreting our positive effects against this backdrop suggests that fidelity matters: the combination of structured rubrics, supportive tone, and immediate turn-around likely increased perceived trustworthiness and usability of the feedback, enabling the psychological pathways discussed above.

The specific measure of persistence used integrates perseverance, affect regulation, and adaptive help-seeking. The observed gains are therefore consistent with a feedback environment that normalizes adaptive help-seeking and reframes errors as signals for adjustment rather than as fixed deficits. In short, contemporary literature and our data converge on a common mechanism: well-designed AI feedback compresses the feedback loop and lowers evaluative threat, which strengthens competence beliefs and emotion regulation, and in turn yields higher frustration tolerance and more durable persistence.

CONCLUSION

This study examined whether an AI-driven feedback system—engineered to deliver immediate, specific, and supportive guidance—can strengthen Chinese university students' frustration tolerance and learning persistence. Across a six-week intervention, students who received AI feedback exhibited statistically significant improvements on both outcomes, whereas peers receiving delayed summary feedback did not. Manipulation checks confirmed the fidelity of the intervention, indicating that the observed effects can be attributed to the intended qualities of the feedback rather than to ancillary features of the learning environment. From a practical standpoint, the study suggests that AI feedback systems should be designed to deliver real-time, detailed, and encouraging feedback to maximise benefits for student resilience. Educators can integrate such systems to complement traditional feedback mechanisms, thereby supporting students' emotional coping strategies and sustained engagement with challenging tasks. In contexts where large class sizes and limited teacher–student interaction time constrain personalised feedback, AI systems offer a scalable solution for maintaining the quality and timeliness of formative assessment.

LIMITATIONS AND FUTURE RESEARCH

Several constraints should be acknowledged. First, the study was conducted in a single institution and focused on a single task domain. This limits external validity; effects may differ across disciplines, course formats, and institutional cultures. Second, although the design used stratified random assignment and blinded human rating of end products, participants themselves could not be blinded to condition. This raises the possibility of expectancy effects and contamination (e.g., control students informally consulting AI tools), despite our compliance checks.

Future studies should pursue multi-site, cluster-randomised trials spanning diverse disciplines to test generalisability, with longer follow to assess maintenance and transfer. To move beyond bundled treatments, employ factorial experiments or micro-randomised trials designs that randomise feedback features at the message level, enabling estimation of proximal causal effects and optimal sequencing. Methodologically, pair self-reports with behavioural and performance indicators (completion rates, revision counts, latency to resubmission, rubric-based achievement) and, where appropriate, physiological or affective signals to triangulate mechanisms.

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