

Human-Centered AI in Practice: Peer Facilitators as Technostress Reducers in a Mixed-Methods LMS Study

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Abstract

Purpose: While the rapid integration of generative artificial intelligence (AI) offers significant pedagogical potential, it often outpaces the psychological scaffolding that anxious learners require, creating a severe affective barrier known as technostress. To address this critical gap, this study investigates whether structured peer facilitation, embedded within a Learning Management System (LMS) based AI course, can effectively reduce undergraduate students' AI anxiety and strengthen their conceptual understanding.

Methods/Study design/approach:

An explanatory sequential mixed-methods design was conducted involving 33 undergraduate students encountering generative AI instruction for the first time. Quantitative data encompassing AI anxiety, conceptual understanding, and technical self-efficacy were collected pre- and post-intervention, followed by analysis using Wilcoxon signed-rank tests and Spearman's rank correlation. Subsequently, qualitative data from open-ended evaluations were examined through reflexive thematic analysis to contextualize and deeply explain the quantitative shifts.

Result/Findings:

The intervention yielded a statistically significant reduction in AI anxiety ($Z = -2.151$, $p = .032$) alongside a significant improvement in conceptual understanding ($Z = -1.990$, $p = .047$). Although technical self-efficacy and career projection improved, the changes did not reach statistical significance. Furthermore, facilitator evaluation exhibited a significant negative correlation with anxiety reduction ($r_s = -.389$). Thematic analysis confirmed that peer facilitators effectively acted as technical translators and technostress reducers, establishing the psychological safety necessary for learning.

Novelty/Originality/Value:

This research uniquely repositions peer mediation as the vital affective "more capable other" within Vygotsky's Zone of Proximal Development, prioritizing the resolution of emotional barriers before cognitive engagement with AI tools. The study extends Human-Centered AI (HCAI) theory by delivering robust empirical evidence that pairing generative AI modules with human peer facilitation creates a synergistic learning ecosystem. This provides educators with a scalable, practical solution for mitigating technostress in modern digital education.

Keywords: AI anxiety, Generative artificial intelligence, Human-centered AI, Peer facilitation, Zone of proximal development

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INTRODUCTION

The unprecedented proliferation of generative artificial intelligence (AI) within higher education has occurred at a velocity that frequently outstrips institutional readiness. Within a span of only a few academic years, tools capable of producing fluent text, code, and explanations on demand have transitioned from mere novelties to ubiquitous elements of undergraduate coursework [1], [2]. This rapid uptake has generated a substantial body of literature documenting students' generally favorable attitudes toward generative AI as a versatile learning companion, particularly for tasks such as drafting, brainstorming, and locating information [3], [4]. However, enthusiasm at the attitudinal level does not necessarily translate into competence or comfort at the practical level, especially among learners who are simultaneously expected to comprehend the underlying mechanics of the technology rather than merely consume its outputs [5].

Scholars examining the pedagogical promise of generative AI have emphasized its capacity to personalize instruction, scaffold problem-solving, and extend the range of tasks a learner can accomplish with

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appropriate support [6], [7]. Framed through Vygotsky's notion of the zone of proximal development (ZPD), AI tools have been theorized as a form of digital scaffold that narrows the distance between what a student can achieve unaided and what becomes possible with algorithmic guidance [8], [9]. Recent developments in AI-based educational platforms have demonstrated the practical viability of utilizing such digital scaffolds to navigate complex cognitive tasks [10]. This optimistic reading, however, is strictly conditioned on the assumption that learners approach the technology with sufficient baseline confidence to engage with it productively - an assumption that recent empirical evidence increasingly calls into question [11].

A parallel and less celebratory strand of research has documented a distinct psychological barrier that complicates this pedagogical landscape: AI anxiety, defined as an emotional state encompassing fear of the unfamiliar mechanics of AI systems and apprehension regarding one's own capacity to utilize them appropriately [12]. Distinct from generalized computer anxiety, AI anxiety is inextricably linked to the perceived opacity and autonomous nature of machine-generated outputs [13]. This anxiety operates as a severe affective barrier. Saleem et al. [14] demonstrated that technostress, triggered by rapid technological shifts in academic settings, significantly impairs cognitive processing and academic resilience.

When students experience high levels of AI anxiety, their cognitive load exponentially increases, thereby inhibiting their ability to engage productively with learning management systems (LMS) designed to teach these very tools. Mitigating such cognitive overload requires intentional, empathetic design strategies that simplify interactions and prioritize affective support over sheer technical complexity [15]. Furthermore, Wang and Chuang [16] clarified that overcoming this initial anxiety is an absolute prerequisite to building technical self-efficacy. Because self-efficacy requires repeated mastery experiences, a highly anxious student is likely to avoid the technology entirely, preventing any mastery experiences from occurring [17].

One pedagogical mechanism long recognized for supplying responsive, socially embedded support is peer facilitation. Systematic evidence indicates that peer-assisted learning arrangements yield measurable benefits for emotional and psychological outcomes, including significantly reduced anxiety and increased academic belonging [18], [19]. In the specific context of integrating AI into instruction, a recent systematic review of AI-supported peer learning concluded that the deliberate pairing of artificial intelligence with human peer support remains comparatively underexplored [20], [21], [22].

To date, a few researchers have focused on the theoretical potential of AI tools as cognitive scaffolds [8], [9], while others have explored the psychological barriers of AI anxiety in isolated contexts [12]. However, there have been limited studies concerned with deliberately embedding structured peer facilitation within an LMS-based introductory AI course to function as an affective scaffold. Therefore, this research intends to investigate the precise effect of structured peer facilitation on undergraduate students' AI anxiety, conceptual understanding of AI, technical self-efficacy, and career projection. The objectives of this research are to evaluate pre- and post-intervention differences quantitatively and to explain the underlying psychological mechanisms qualitatively, thereby extending Human-Centered AI (HCAI) theory by positioning human mediation as an irreplaceable component within the digital learning ecosystem.

METHODS

This study adopted an explanatory sequential mixed methods design to ensure methodological rigor [23]. In this specific framework, an initial phase of quantitative data collection and analysis is systematically followed by a second, interpretive phase of qualitative data collection [24]. This sequence is intentionally designed to explain and contextualize the quantitative patterns observed during the primary phase [25], [26]. The explanatory sequential design was selected because answering the central research question required robust statistical evidence of change to be analyzed alongside the participants' own phenomenological accounts of the facilitation experience [27].

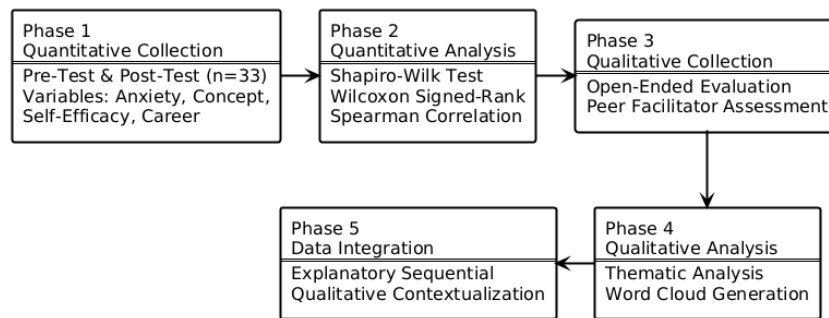


Figure 1. Mixed Methods Flowchart

The research was conducted in a higher education setting, specifically targeting an introductory course on artificial intelligence concepts. The course was delivered entirely through an institutional learning management system (LMS). Participants were 33 undergraduate students distributed across their second ($n = 10$), fourth ($n = 12$), and sixth ($n = 11$) semesters. A purposive sampling technique was utilized based on strict inclusion and exclusion criteria. The inclusion criteria required participants to be active undergraduate students enrolled in the introductory AI course who were encountering formal generative artificial intelligence instruction for the first time within a highly structured online environment. Conversely, students with advanced programming backgrounds or prior formal AI training were excluded to ensure a homogenous baseline regarding AI anxiety.

Participants were recruited voluntarily through a formal announcement posted on the course's LMS during the first week of the academic term. The sample size of 33 represents the entire enrolled cohort of this specific pilot class. While this relatively small sample limits broad generalizability, it is statistically sufficient for the non-parametric Wilcoxon signed-rank tests employed in this study. Furthermore, keeping the sample size at 33 aligns with the explanatory sequential mixed-methods design, allowing for a manageable scale to conduct rigorous, in-depth qualitative thematic analysis of the participants' experiences. Table 1 summarizes the demographic profiles of the participants.

Table 1. Participant Demographic Profile

Characteristic	Category	n	%
Age	19-20 years	18	54.5
	21-22 years	15	45.5
Gender	Male	18	54.5
	Female	15	45.5
Study Year*	2nd Semester	10	30.3
	4th Semester	12	36.4
	6th Semester	11	33.3
Prior Generative AI Exposure	Yes	20	60.6
	No	13	39.4

The intervention procedure involved the seamless integration of a structured peer facilitation mechanism into the existing LMS. Upper-level undergraduate students with prior expertise in artificial intelligence integration were recruited and explicitly briefed to act as peer facilitators. Their primary pedagogical role was not to deliver new cognitive content, but rather to translate complex technical jargon and foster a psychologically safe discussion space.

Quantitative data were gathered using self-report questionnaires administered via the online platform immediately before and after the facilitation period. AI anxiety was measured using items adapted from the validated Artificial Intelligence Anxiety Scale [12]. Technical self-efficacy and career projection were assessed using items adapted from established AI self-efficacy instrumentation [16]. The conceptual understanding of artificial intelligence was evaluated utilizing a structured content-knowledge test strictly aligned with the formal learning objectives of the course. The normality of the four continuous outcome variables was rigorously assessed using the Shapiro-Wilk test [28]. Consequently, non-parametric Wilcoxon signed-rank tests were employed to evaluate the pre- and post-intervention differences, and Spearman rank-order correlation was utilized to test the association between the students' evaluation of the peer facilitator and anxiety change scores. For the qualitative phase, responses from the open-ended evaluations were analyzed using reflexive thematic analysis [29].

RESULT AND DISCUSSION

Prior to substantive hypothesis testing, the distribution of each outcome variable was examined using the Shapiro-Wilk test, summarized in Table 2. Across all four outcome variables, the test indicated a significant departure from normality ($p < .05$). This statistical violation justified the use of non-parametric Wilcoxon signed-rank tests for pre-post comparisons.

Table 2. Shapiro-Wilk Normality Test Results

Variable (Pre/Post)	n	Statistic (W)	p	Distribution
AI Anxiety (Pre)	33	.898	.005*	Not normal
AI Anxiety (Post)	33	.900	.005*	Not normal
AI Concepts (Pre)	33	.803	< .001*	Not normal
AI Concepts (Post)	33	.689	< .001*	Not normal
Self-Efficacy (Pre)	33	.803	< .001*	Not normal
Career Projection (Pre)	33	.829	< .001*	Not normal

Table 3 presents the results of the Wilcoxon signed-rank tests. AI anxiety decreased significantly following the peer facilitation intervention ($Z = -2.151$, $p = .032$), and the associated effect size ($r = .265$) indicates a practically meaningful impact within the affective domain. Understanding of basic AI concepts also improved significantly ($Z = -1.990$, $p = .047$), suggesting that robust conceptual gains can be reliably replicated within a peer-mediated LMS delivery model.

Table 3. Wilcoxon Signed-Rank Test Results

Variable	n	Z	p	Cohen's r	Decision
AI Anxiety	33	-2.151	.032*	.265	Sig. decrease
Basic AI Concepts	33	-1.990	.047*	.245	Sig. increase
Technical Self-Efficacy	33	-1.342	.180	.165	n.s.
Career Projection	33	-.587	.557	.072	n.s.

To visually illustrate the magnitude and distribution of this affective shift, Figure 2 displays a violin plot detailing the reduction in AI anxiety. This visualization captures not only the overall downward shift in anxiety scores but also the changing density of the data, indicating a more uniform sense of psychological relief among the participants post-intervention.



Figure 2. Violin Plot of AI Anxiety Reduction

Concurrently, to represent the cognitive dimension of the intervention, Figure 3 presents a bar chart outlining the conceptual improvements. The chart emphasizes the tangible upward trajectory in the students' understanding of basic artificial intelligence concepts following the peer-facilitated sessions.

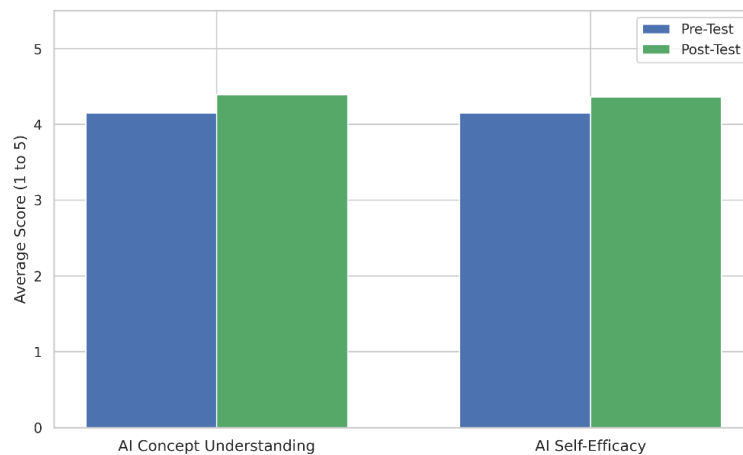


Figure 3. Bar Chart of Cognitive Improvements

In contrast, technical self-efficacy and career projection did not reach conventional levels of statistical significance. This divergence between the affective outcome and the self-evaluative outcomes is theoretically highly informative. AI anxiety appears responsive to immediate social reassurance, whereas self-efficacy requires repeated, evaluated mastery experiences across multiple occasions [16].

The relationship between facilitator quality and affective change was examined further through Spearman rank correlation. As presented in Table 4, a significant negative correlation was found between students' evaluation of their peer facilitator's performance and the magnitude of decrease in their AI anxiety scores ($r_s = -.389$, $p = .025$). This robustly indicates that better-perceived facilitation is directly associated with greater anxiety relief.

Table 4. Spearman Rank-Order Correlation Results

Variable 1	Variable 2	n	r_s	p
Facilitator Evaluation	Δ AI Anxiety (pre-post)	33	-.389	.025*

Open-ended evaluations of the peer facilitation experience were analyzed thematically. The most frequent terms across responses were 'helpful', 'discussion', 'relaxed', and 'peer'. The prominence of 'relaxed' alongside 'helpful' is particularly notable: students' language gravitated toward the emotional register of the interaction, entirely consistent with the quantitative finding that anxiety shifted significantly while self-efficacy did not [29].



Figure 4. Word cloud of peer facilitator evaluation

As visualized in Figure 4, the most frequent terms emerging from the raw qualitative data include membantu (helpful), santai (relaxed), diskusi (discussion), and teman sebaya (peers). The data explicitly highlights how peer facilitators masterfully addressed the cognitive barrier. Rather than acting strictly as authoritative sources delivering more technical content than the LMS modules already contained, they translated complex content into familiar terms and normalized confusion as an expected, acceptable part of the learning process [13].

This pattern highlights the facilitator's critical value as a pedagogical bridge, functioning simultaneously as a technical translator and an emotional anchor - a finding highly consistent with broader peer-assisted learning literature [19], [20]. The theoretical model emerging from these mixed-methods findings centers on Vygotsky's zone of proximal development (ZPD). Where prior accounts have often positioned the AI tool itself as the exclusive "more capable other" [8], the present findings suggest a more nuanced, layered structure.

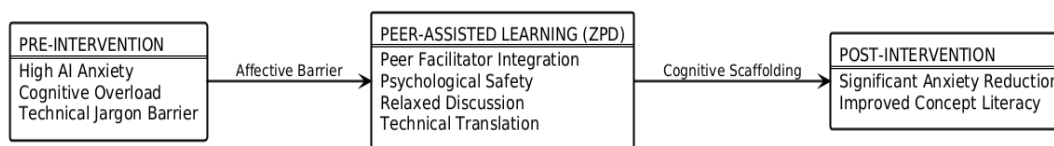


Figure 5. Conceptual framework

Within this framework, the peer facilitator occupies the position of the "more capable other" with respect to the affective barrier (AI anxiety), while the AI tool remains the "more capable other" with respect to the cognitive barrier. This layered interpretation aligns flawlessly with Human-Centered AI (HCAI) theorizing, which asserts that technological systems should be designed and deployed in ways that strengthen rather than substitute for human judgment, relationship, and empathetic support [30].

CONCLUSION

This study empirically examined whether structured peer facilitation embedded within an LMS-based introductory artificial intelligence course could effectively mitigate undergraduate students' AI anxiety while simultaneously strengthening their conceptual understanding. The findings revealed a statistically significant reduction in AI anxiety and a significant improvement in conceptual understanding following the intervention. While technical self-efficacy and career projection exhibited positive improvements, they did not reach statistical significance. Thematic analysis elucidated that peer facilitators primarily functioned as indispensable technical translators and technostress reducers, establishing a psychologically safe learning space. These integrated findings significantly extend contemporary Human-Centered Artificial Intelligence (HCAI) theorizing by repositioning human peer mediation as the operative "more capable other" strictly necessary for addressing the affective dimensions of a learner's zone of proximal development. The study robustly demonstrates that before students can productively utilize generative AI for cognitive advancement, they must first overcome the profound emotional barriers associated with technostress. Consequently, this research provides educators with a scalable, highly practical pedagogical framework, proving that pairing advanced AI tools with empathetic human facilitation creates a resilient and synergistic digital education ecosystem.

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