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Amplified Intelligence in the Classroom: An Exploratory Study of Generative AI's Psychological and Pedagogical Effects

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Abstract

In this study, we employed a quasi-experimental design with a 2×2 factorial framework to investigate the effects of using Generative Artificial Intelligence (GenAI)-based tools on student stress, anxiety, understanding, and perceived fairness during authentic classroom learning experiences in higher education. We analyzed data from the validated and exploratory analyses in two stages. Across both analyses, results suggested that GenAI systems function as both cognitive and emotional supplements, enhancing users' mental health and deepening their understanding of the learning material. The results of the exploratory analysis also indicated improvements in perceived fairness and equity among peers. The results of this study could offer preliminary implications for higher education leaders and scholars. Our results offer insights into faculty development, instructional design, and curriculum changes to train students for a GenAI-mediated world of work.

Keywords: Generative AI; Higher Education; Prompt Literacy; Student Well-Being; Human-AI Collaboration; Technology Acceptance

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1. Introduction

The growing implementation of Generative Artificial Intelligence (GenAI) in educational tools prompts important discussions about how it affects students' cognitive processes and emotional experiences and poses ethical challenges in educational contexts. While traditional studies have primarily focused on task efficiency and learning outcomes, new research examines how GenAI affects students' mental health, their academic self-beliefs, and their views on fairness (Williamson & Eynon, 2020; Clark et al., 2016). However, real-world, classroom-based evidence remains limited. A systematic review by Zawacki-Richter et al. (2019) confirms that while AI research in education is growing, most studies are conceptual or simulation-based, with a scarcity of empirical, classroom-based interventions.

Recent scholarship on GenAI in higher education has emphasized academic integrity, assessment redesign, and institutional policy responses (Bittle & El-Gayar, 2025; Francis et al., 2025). Those conversations are important, but they are limited in terms of explaining how students experience GenAI while completing authentic course assignments in live classroom settings. Also, there remains limited empirical evidence on whether course-embedded GenAI support affects students' stress, anxiety, mental well-being, perceived understanding, perceived output quality, and fairness-related perceptions during assignment completion.

This study addresses that gap by examining GenAI through the lens of Amplified Intelligence, which treats AI as a *tool* for human cognitive enhancement rather than as a *replacement* (Brynjolfsson & McAfee, 2014; Shrestha et al., 2019). Guided by this perspective, this study investigates whether GenAI-supported assignment workflows are associated with differences in students' psychological well-being, learning-related perceptions, and fairness-related perceptions in an undergraduate classroom context. This focus is important because institutions are now making decisions about whether, when, and how to integrate GenAI into teaching. Evidence from authentic classroom settings can help instructors and administrators move beyond abstract debate and toward more informed decisions about course design, student support, and responsible implementation. Accordingly, this study addresses the following research question:

- *What are the influences of GenAI support during authentic course assignments on students' psychological well-being, learning-related perceptions, and fairness-related perceptions, in a face-to-face university classroom setting?*

2. Literature Review

Before the rise of GenAI, research on artificial intelligence in higher education had already established AI as an important educational technology topic, although much of that earlier literature focused on broader AI applications rather than generative tools specifically (Zawacki-Richter et al., 2019). Since the public release of ChatGPT, GenAI has intensified scholarly attention around teaching, learning, assessment, and institutional adaptation, leading to a rapid expansion of higher education research in this area (Qian, 2025).

A growing line of research suggests that students often perceive GenAI as useful for brainstorming, writing support, feedback, and learning assistance (Chan & Hu, 2023). At the same time, those perceived benefits are accompanied by concerns about accuracy, overreliance, and the quality of student thinking (Kasneci et al., 2023). This tension underscores the importance of examining GenAI not only as a productivity tool but also as a classroom support mechanism that may affect how students experience assignment completion. Although AI is increasingly embedded in higher education, its impact on student well-being remains underexplored (Klimova & Pikhart, 2025). Recent review work suggests that AI may support students through personalization and efficiency, but it may also introduce digital fatigue, technostress, anxiety, and new forms of dependency (Klimova & Pikhart, 2025). As a result, psychological outcomes such as stress, anxiety, and mental well-being deserve more direct empirical attention in classroom-based GenAI studies.

GenAI in higher education also raises questions about fairness, equity, and access. Recent reviews and surveys highlight concerns about bias, the digital divide, and uneven readiness or comfort across student groups. Taken together, the literature suggests a clear need for empirical classroom studies that examine psychological well-being, learning-related perceptions, and fairness-related perceptions together during authentic academic work rather than in hypothetical or policy-only discussions (Francis et al., 2025; Maxwell et al., 2025).

3. Theoretical Background

By combining Amplified Intelligence, the Technology Acceptance Model (TAM), and Extended Cognition theories, this research explains how GenAI systems affect students' psychological well-being, learning outcomes, and perceptions of fairness. The study design relies on these frameworks to interpret the effects observed during GenAI-supported assignments.

Amplified Intelligence frames AI as a tool that augments human cognition rather than replaces human judgment (Brynjolfsson & McAfee, 2014; Shrestha et al., 2019). In educational settings, this perspective is useful because it positions GenAI as a scaffold that can help students manage complexity, reduce ambiguity, and improve clarity while preserving student agency. Under this view, GenAI support may influence psychological outcomes by reducing cognitive strain during demanding assignments, and it may influence learning-related outcomes by helping students better understand what they are trying to do and how to do it. The Technology Acceptance Model (TAM) helps explain why students are more likely to use technology when they perceive it as useful and easy to use (Venkatesh & Davis, 2000). In a classroom setting, these perceptions matter because they shape whether students experience GenAI as supportive, frustrating, trustworthy, or intrusive. TAM helps explain why GenAI support may affect not only students' willingness to use the tool but also their perceptions of learning quality, confidence, and classroom support. Extended Cognition suggests that tools can become part of a person's cognitive process when they are integrated into ongoing problem-solving (Clark & Chalmers, 1998). In the context of coursework, GenAI may serve as a cognitive extension, helping students externalize part of the planning, drafting, or clarification process. If students experience GenAI as part of their work problem-solving environment, the tool may affect not only task performance but also emotional experiences, such as stress reduction and perceived support during difficult academic work.

Taken together, these three theoretical perspectives support an integrative view of GenAI in classroom settings. Amplified Intelligence explains why GenAI may reduce cognitive burden and improve perceived clarity. TAM explains why perceived usefulness and ease of use may shape students' responses to the tool. Extended Cognition explains why GenAI may become part of students' active problem-solving process during assignment completion. Accordingly, this study organizes its outcome variables into three families: psychological well-being, learning-related perceptions, and fairness-related perceptions. Figure 1 presents this theory-informed integrative model. Importantly, the model is presented as a conceptual framework for interpreting the study's findings rather than as a formally tested structural, mediation, or moderation model.

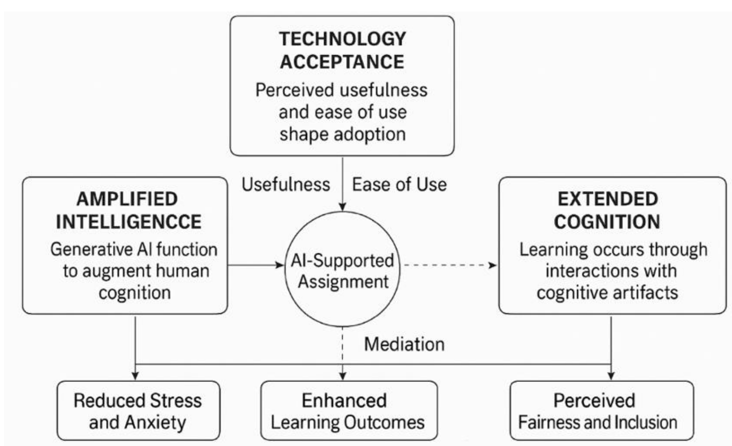

Figure 1: Research Framework

4. Methodology

4.1 Research Setting and Design

This study was conducted in an undergraduate Information Systems class using a quasi-experimental 2×2 factorial design. This study examines the impact of GenAI-assisted assignment tools on students' psychological well-being, learning-related perceptions, and fairness-related perceptions. The study implemented a dual-phase analytical approach (Shadish et al., 2002). Phase 1 used a strictly verified subset of observations to prioritize internal validity. Phase 2 used a larger set of inferred assignment-level observations to examine whether the Phase 1 pattern persisted in a broader classroom dataset.

4.2 Experimental Setting and Assignment Conditions

The course included multiple assignment opportunities completed under two instructional conditions: (1) GenAI-supported assignments, in which students had access to a course-provided ChatGPT-enabled interface through Canvas, and (2) non-GenAI assignments, in which students completed the work without course-provided GenAI support. Assignments varied in format, including structured form-based tasks and open-ended narrative tasks. Because the assignment type was not modeled as a focal independent variable in the analyses reported in this paper, it is described here as part of the instructional context rather than as a tested factor in the final statistical results.

The primary unit of analysis was the student in Phase 1 and the assignment observation in Phase 2, with Phase 2 observations contributed by students across multiple assignments.

4.3 Phase 1: Exploratory Analysis

Phase 1 prioritized internal validity by restricting the analysis to a subset of observations for which exposure status could be clearly verified. This phase included 35 verified cases. Exposure status was confirmed using three sources: (1) Canvas access logs for GenAI tool usage, (2) section rosters and assignment time stamps, and (3) manual matching of student identifiers to assignment conditions. Only cases with clear and consistent evidence across these sources were retained in the Phase 1 dataset.

The verified control group in Phase 1 was small ($n = 6$). This limitation reduces statistical power and constrains generalizability, so Phase 1 should be interpreted as a conservative exploratory analysis rather than as definitive evidence.

4.4 Phase 2: Repeated-measures Analysis

Phase 2 expanded the analysis to 346 assignment observations drawn from the broader classroom dataset. Because direct verification was not feasible for all observations, exposure status was inferred using a conservative heuristic classification process. An assignment was classified as GenAI-supported when two or more of the following conditions were met: (1) the assignment was submitted from a Canvas environment with GenAI features, (2) system logs indicated GenAI tool use within a 30-minute window surrounding submission, and (3) the student reported GenAI use in the post-assignment survey.

An assignment was classified as non-GenAI-supported when one or more of the following conditions were met: (1) the assignment was submitted in a course section that was not assigned GenAI access, (2) neither system logs nor the post-assignment survey indicated GenAI use, or (3) the assignment was submitted outside designated GenAI access windows. Observations with ambiguous evidence were excluded from Phase 2 to preserve a more conservative classification process. Importantly, non-GenAI-supported in Phase 2 should be interpreted as non-course-supported rather than as proof of zero outside AI use, because students may have had access to personal GenAI tools beyond the course environment.

4.5 Survey Measures

Post-assignment surveys measured three families of outcomes: psychological well-being, learning-related perceptions, and fairness-related perceptions. Psychological well-being was measured using items related to stress, anxiety, and mental well-being. Learning-related perceptions were measured using items related to understanding, output quality, and goal clarity. Fairness-related perceptions were measured using items assessing support for fairness and peer equality.

All measures used a 7-point Likert scale, with higher values indicating more favorable outcomes. To create the Psychological Well-Being Index, stress and anxiety items were reverse-coded so that higher index values reflected lower psychological strain. Table 1 presents the construct definitions, variable mapping, and reliability estimates.

Construct	Item Code(s)	Example Item	Cronbach's α
Psychological Well-Being Index	Stress anxiety mental well-being	"Using GenAI improved my mental well-being compared to not using GenAI."	0.81
Learning-Related Perceptions Index	understanding output quality goal clarity	"I understood the course material better with GenAI."	0.79
Fairness-Related Perceptions Index	support fairness peer equality	"Using GenAI made the learning environment fairer and more inclusive."	0.75

Table 1. Survey Items and Construct Mapping

Note. Higher values indicate more favorable outcomes. Stress and anxiety items were reverse-coded before the Psychological Well-Being Index was computed.

4.6 Missing Data and Processing

During data preparation, surveys and assignment records were matched using Stata-assisted identifier reconciliation. Minor variations in student identifiers (e.g., abbreviated versus full names) were resolved where possible. Observations that could not be confidently matched were excluded from the dataset, representing less than 5% of the records.

5. Results

5.1 Phase 1: Exploratory Analysis

The effect of GenAI-supported assignments was assessed using data from students who completed all required assignments. Independent-samples t-tests were used to evaluate differences across outcome variables. Descriptive statistics are presented in Table 2, and the corresponding inferential results are presented in Table 3.

Outcome Variable	GenAI Mean (SD)	Control Mean (SD)
Stress	3.19 (1.12)	3.98 (1.21)
Anxiety	2.91 (1.03)	3.75 (1.16)
Mental Well-being	5.52 (0.91)	4.83 (1.02)
Comprehension	5.87 (0.83)	5.06 (0.96)
Output Quality	5.66 (0.88)	4.88 (1.05)
Goal Achievement	5.74 (0.85)	4.94 (1.12)
Fairness/Support	5.42 (0.92)	4.61 (1.09)
Peer Equality	5.31 (0.88)	4.62 (1.01)

Table 2: Descriptive Statistics

Students in the GenAI-supported condition reported lower stress and anxiety and higher mental well-being than students in the non-GenAI condition. These differences were statistically significant for stress ($p = 0.030$), anxiety ($p = 0.015$), and mental well-being ($p = 0.048$). Taken together, these findings suggest that course-embedded GenAI support may reduce psychological strain during assignment completion. Students in the GenAI-supported condition also reported higher understanding, higher perceived output quality, and greater goal clarity than students in the non-GenAI condition.

All three differences were statistically significant (all $p < 0.001$), suggesting that GenAI support was associated with more favorable learning-related perceptions in Phase 1.

No statistically significant differences emerged for support of fairness or peer equality in Phase 1. Although the descriptive statistics favored the GenAI-supported condition, the verified control group was small ($n = 6$), so these null findings should be interpreted cautiously. Accordingly, Phase 1 should be read as a conservative exploratory analysis that provides directional evidence rather than definitive conclusions.

Outcome Category	Variable	GenAI Group Mean	Control Group Mean	*p*-value	Significance
Psychological	Stress	3.12	4.39	0.030	*
	Anxiety	2.95	4.11	0.015	**
	Mental Well-being	5.36	4.42	0.048	*
Learning	Comprehension	5.77	4.91	< 0.001	***
	Output Quality	5.66	4.88	< 0.001	***
	Goal Clarity	5.71	4.94	< 0.001	***
Inclusivity	Fairness	5.11	4.75	0.312	n. s.
	Peer Equality	5.17	4.80	0.281	n. s.

Table 3: Results from Strict Matching Analysis (N = 35)

5.2 Phase 2: Repeated-Measures Analysis

Phase 2 expanded the analysis to 346 assignment observations contributed across multiple assignments. A repeated-measures ANOVA was used to examine whether GenAI support was associated with differences in aggregated outcome indices. The Psychological Well-Being Index was significant ($F = 84.98$, $p < 0.001$), indicating that GenAI-supported assignments were associated with lower psychological strain and stronger reported well-being across repeated observations. This pattern was consistent with the Phase 1 findings and strengthens the interpretation that GenAI support may ease assignment-related stress and anxiety. The Learning-Related Perceptions Index was also significant ($F = 27.11$, $p < 0.001$), indicating that students reported stronger understanding, stronger perceived output quality, and greater goal clarity in the GenAI-supported condition. This pattern again mirrored the Phase 1 results.

Fairness-related outcomes were significant in Phase 2. The support fairness index ($F = 19.02$, $p < 0.001$) and the peer equality index ($F = 16.74$, $p < 0.001$) both favored the GenAI-supported condition. Unlike Phase 1, the larger sample suggests that students may perceive course-provided GenAI support as improving fairness-related conditions in the classroom, although these findings should be interpreted cautiously because exposure status in Phase 2 was inferred rather than directly randomized. See Table 4 for Repeated Measures Results.

Outcome Index	F-value	df	*p*-value	Effect Summary
Psychological Index	84.98	1, 84	< 0.001	GenAI reduced stress/anxiety, increased well-being
Learning Index	27.11	1, 84	< 0.001	GenAI improved comprehension, output, and clarity
Fairness Index	19.02	1, 84	< 0.001	GenAI increased perceived fairness and inclusion
Peer Equality Index	16.74	1, 84	< 0.001	GenAI improved perceptions of equity

Table 4: Repeated Measures Results - Exploratory Analysis (N = 346)

The psychological advantages of GenAI support become evident through visual comparisons. Figure 2 and Figure 3 illustrate distinct differences in stress and mental well-being scores between GenAI-supported and control assignments, with more pronounced trends evident in the exploratory sample. Findings show that GenAI-based tools provide both cognitive and emotional support within academic environments.

Figure 2: Psychological Index (N = 35)

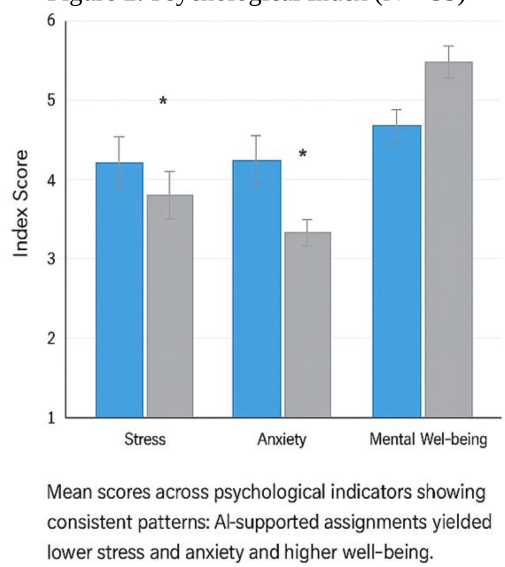

Figure 3: Psychological Index (N = 346)

6. Discussion

This exploratory study examined whether course-embedded GenAI support during authentic assignments was associated with differences in students' psychological well-being, learning-related perceptions, and fairness-related perceptions. Across both analytical phases, the most consistent finding was psychological: students in GenAI-supported conditions reported lower stress and anxiety and stronger mental well-being. Learning-related outcomes also favored the GenAI-supported condition in both phases. Taken together, these findings suggest that GenAI support may serve as a cognitive scaffold, helping students navigate difficult assignments with less strain and greater perceived clarity.

The fairness-related findings were more mixed. Phase 1 did not reveal any statistically significant differences for support of fairness or peer equality, whereas Phase 2 did reveal them. One plausible explanation is statistical power, given the very small, verified control group in Phase 1. Another possibility is that fairness perceptions are especially sensitive to how GenAI access is structured, communicated, and experienced within a course. Students may perceive course-provided GenAI support as fairer when access is visible and integrated, but those perceptions may weaken when access is limited, uneven, or uncertain.

The findings offer preliminary support for the study's integrative theoretical framing. Amplified Intelligence helps explain why students may experience GenAI as cognitive augmentation rather than simple automation. TAM helps explain why perceived usefulness and ease of use may contribute to more favorable learning-related perceptions. Extended Cognition helps explain why students may experience GenAI as part of the problem-solving process itself. However, these findings should be interpreted as being consistent with existing theory, rather than as a definitive confirmation of the full conceptual model.

The practical implications of this study are meaningful and applicable to academic institutions. If institutions choose to embed GenAI tools in coursework, they are expected to pair such access with clear expectations, transparent communication, and instruction in responsible prompt use (Francis et al., 2025; García-López & Trujillo-Liñán, 2025). Faculty development should therefore address not only the technical use of GenAI, but also assignment design, ethical boundaries, and ways to preserve student agency while using AI-supported workflows.

7. Limitations and Future Work

This study has several important limitations. First, Phase 1 included a very small, verified control group, limiting power and generalizability. Second, Phase 2 relied on inferred exposure classification rather than direct random assignment. Third, non-GenAI-supported observations in Phase 2 should be interpreted as non-course-supported rather than as proof that students did not use personal GenAI tools outside the course environment. Fourth, the study was conducted in a single undergraduate course, limiting external validity. For these reasons, the results should be interpreted as preliminary and exploratory rather than as causal or conclusive.

Future research should test these relationships in larger, multi-course designs with clearer randomization or stronger embedded controls. Future studies should also analyze assignment type directly if structured versus open-ended tasks are expected to shape outcomes. In addition, future work should examine longer-term effects, including whether GenAI support influences learning transfer, self-efficacy, overreliance, and changes in perceptions of fairness as institutional norms around AI become more established (Zhai et al., 2024).

8. Conclusion

This study examined whether course-embedded GenAI support was associated with differences in students' psychological well-being, learning-related perceptions, and fairness-related perceptions during authentic assignment work. Across both analytical phases, the clearest and most consistent pattern was that GenAI-supported assignments were associated with lower reported stress and anxiety and with more favorable learning-related perceptions. Fairness-related outcomes were more mixed across phases, suggesting that this domain may depend more heavily on the implementation of conditions and measurement context. Overall, the study offers preliminary evidence that GenAI can function as amplified intelligence in classroom settings, while underscoring the need for more rigorous, multi-course research before strong causal claims are made.

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