Technostress in Hybrid Intelligence: A Mixed-Methods Study of Human-AI Teaming in Higher Education

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Abstract

The rapid integration of Artificial Intelligence (AI) in higher-education learning environments holds significant transformative potential. AI offers substantial pedagogical and organizational benefits, yet it also introduces psychological and physiological pressures as students are required to continuously adapt to increasingly technology-integrated learning conditions. These pressures are often conceptualized as technostress. This study aims to examine technostress in the context of human-AI collaboration, in which pairs of students work with a generative AI functioning as a third team member. Using a mixed-methods design, 150 undergraduates first completed a standardized technostress survey to measure baseline levels and dimensions of technostress, followed by pairs of participants completed a task with speech-based generative AI agent, and semi-structured interviews probing experiences, perceived technostressors, and adaptive responses. By situating the investigation within an authentic, co-evolutionary Hybrid Intelligence setting, where pairs of students must interpret, negotiate, and integrate AI-generated contributions, the study reveals forms of technostress that remain unobservable in traditional dyadic human-AI studies or survey-based adoption research. The findings are expected to offer theoretical contributions by refining current understandings of technostress in multi-human, AI-supported collaboration; methodological contributions by introducing an empirically grounded approach for examining stress in collaborative Hybrid Intelligence tasks; and practical contributions by informing the design of AI environments and institutional guidelines that promote supportive, low-strain learning conditions in higher education.

Keywords

Hybrid intelligence, Human–AI teams, Technostress, Technostressors, Coping responses

1. Introduction

The emergence of Hybrid Intelligence (HI) positions human–Artificial Intelligence (AI) collaboration as a central driver of future learning ecosystems, emphasizing mutual co-learning between human cognition and machine capabilities [1]. As societies transition toward complex AI-integrated learning environments, learners are increasingly required to cultivate higher-order skills such as adaptability, critical evaluation, digital literacies, and socio-emotional regulation. In parallel, AI systems continue to improve through interaction with human input, learning from user behavior, refining linguistic outputs, and adapting to contextual cues, thereby enhancing their capacity to function as collaborative partners in cognitive tasks [2]. When effectively aligned, this reciprocal development supports richer learning experiences, enabling learners to externalize cognitive load, receive personalized feedback, and engage in more sophisticated sense-making processes [3]. HI becomes especially visible in collaborative learning tasks, where students and generative models engage in iterative cycles of prompting, evaluating, and revising. This process distributes cognitive labor while requiring constant monitoring and judgment [4, 5]. Although these interactions can reduce cognitive load and provide linguistic scaffolding, the unpredictability, opacity, and occasional inaccuracy of AI outputs introduce additional evaluative

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demands that may heighten uncertainty, doubt, and emotional strain [6, 7, 8]. Thus, the success of human–AI co-learning depends on learners' ability to effectively interact with AI systems [9].

However, learners' capacity to sustain productive co-learning with AI can be undermined by challenges inherent to technology use. Technostress, conceptualized as a negative psychological response to technological demands and complexities, poses a significant risk to this process [10]. Elevated technostress may undermine the very skills HI aims to foster by increasing anxiety, reducing cognitive resources, and limiting learners' willingness to engage with AI tools [8]. Understanding how such collaborations elicit technostress is therefore essential to ensure that human–AI collaboration contributes to, rather than hinders, learners' long-term development. Despite this importance, existing research on technostress in human–AI contexts remains limited. Most studies focus on dyadic interactions between a single human and an AI system rather than multi-human collaborative settings. Reviews highlight that current research rarely examines intragroup processes when AI is embedded within teams, leaving significant theoretical and methodological gaps in understanding shared reasoning, decision-making, and co-construction processes [11, 12].

Within higher education, generative AI is typically conceptualized as an individual learning aid for information retrieval, idea generation, feedback, or task scaffolding, rather than as an active team member shaping group interaction [13, 14]. Nevertheless, contemporary European funding calls and ongoing research increasingly frame human-AI collaboration in terms of AI serving as a collaborative team member, making it essential to examine the phenomenon through this lens. However, collaborative scenarios in which pairs of students jointly engage with a shared AI agent to negotiate meanings, construct arguments, and co-design learning solutions are largely unexplored [8]. This absence is particularly salient given increasing concerns about technostress, defined as the negative psychological response to technology demands and uncertainties [15], which may intensify in human-AI teams as learners must manage not only interpersonal collaboration but also the unpredictability, ambiguity, and cognitive load introduced by AI systems. In addition, studies on human-AI interactions in collaborative learning tend to emphasize attitudes, usefulness, and behavioral intention, often relying on surveys and self-reports that offer limited insight into learners' stress experiences, coping strategies, or moment-to-moment interactions with AI tools [6, 8]. Although recent work links AI-related technostress to discontinuance intentions and well-being, these relationships are rarely examined within authentic academic tasks [10]. Reviews also highlight the need for empirically grounded design guidance for AI-rich learning environments, yet task-level insights remain underdeveloped [16]. As a result, little is known about how student pairs collaborate with an AI teammate during learning tasks, or how such interactions shape learners' technostress within emerging HI learning environments.

To address these gaps, the present study investigates technostress in human–AI collaboration within an authentic higher education task. Specifically, the study addresses the following research questions:

- RQ1: What levels of technostress are present across different dimensions (e.g., techno-overload, techno-complexity, techno-uncertainty) in human–AI collaboration during a learning task?
- RQ2: What technostressors do learners report encountering during human–AI collaboration in the learning task?
- RQ3: What coping mechanisms and adaptive strategies do learners use to regulate technostress when collaborating with other learners and AI?

The objective of this study is to advance empirical understanding of technostress within emerging HI learning environments by examining how pairs of students collaborate with a generative AI agent as a third team member during an authentic academic task. A mixed-methods design is employed, integrating quantitative technostress surveys administered at multiple time points (pre-task, interval, and post-task) with post-task semi-structured interviews. By grounding the investigation in an authentic, co-evolutionary HI context, where learners evaluate, negotiate, and integrate AI contributions while coordinating with peers, the study captures forms of technostress that remain unobservable in traditional dyadic or purely self-report-based research. The findings are expected to contribute theoretically by refining understandings of technostress in multi-human AI-supported collaboration, methodologically by offering an empirically grounded approach for studying stress in HI tasks, and practically by informing the design of supportive, low-strain AI-rich learning environments in higher education.

2. Background

2.1. Hybrid Intelligence and Human–AI Co-evolution

Hybrid Intelligence (HI) conceptualizes learning as a co-evolutionary process in which human cognition and AI systems mutually augment one another. Rather than viewing AI as a replacement for human thinking, HI emphasizes collaborative problem-solving, shared regulation, and distributed cognitive labor, where each partner contributes complementary strengths [4, 2]. In higher education, this perspective has become increasingly relevant as generative AI tools such as ChatGPT and Gemini participate in key academic tasks by supporting brainstorming, generating linguistic structures, and facilitating meaning-making. These developments position task-level human–AI collaboration as a core mechanism through which HI becomes operational. During collaborative human–AI learning tasks, students engage in iterative cycles of prompting, evaluating, integrating, and revising AI-generated content. Such activities reflect shared regulatory processes in which humans monitor quality and coherence, while AI provides alternative formulations, suggestions, and scaffolds. Research indicates that these interactions can enhance accessibility, reduce cognitive load, and improve performance, but may also introduce confusion, emotional strain, and uncertainty when AI outputs appear unpredictable or overly authoritative [6]. Because HI depends on learners' ability to engage productively and confidently with AI, psychological factors such as technostress become central to its success. When students experience overload, complexity, or uncertainty, these stressors may disrupt regulatory processes, reduce cognitive resources, and limit the benefits of human–AI co-evolution. Thus, examining how students experience technostress while collaborating with AI is essential for understanding when HI enhances learning and when stress undermines the developmental gains it aims to support.

2.2. Technostress in AI and Hybrid Intelligence

The rapid expansion of AI in education has intensified concerns regarding technostress, defined as the negative psychological relationship individuals develop in response to technological demands, uncertainties, or mismatches between user capabilities and system complexity [15]. Research in workplace human–AI collaboration similarly indicates that technostress—particularly experiences of complexity when interacting with AI—can diminish perceived ease of use and undermine effective engagement with AI systems [17]. Studies consistently show that AI adoption can heighten anxiety, fatigue, and cognitive strain, especially when learners must navigate opaque algorithms or unpredictable system behaviors [18, 8]. Recent work examining AI applications in smart environments demonstrates that generative AI may trigger technostress across multiple dimensions, including techno-overload, techno-complexity, techno-uncertainty, and techno-insecurity, particularly when users must interpret or correct AI-generated outputs [19]. Evidence from higher education contexts further highlights emerging technostress associated with AI-based tools, where learners report increased anxiety, frustration, and reduced productivity as they adapt to rapidly evolving technologies [20]. Within collaborative learning contexts, these pressures may be amplified. HI teamwork requires learners not only to interact with AI outputs but also to negotiate meaning with peers, evaluate reliability, and coordinate joint decision-making. These demands position technostress as a critical factor influencing whether human–AI collaboration supports or disrupts co-construction, cognitive offloading, and the co-evolutionary processes central to HI.

3. Method

3.1. Research Design

This study employed a mixed-methods design consisting of (a) quantitative self-report surveys administered at multiple time points to capture students' technostress before, during, and after human–AI collaboration, and (b) post-task semi-structured interviews to explore students' experiences in depth. The collaborative component required pairs of university students to work jointly with a generative AI system (Gemini or ChatGPT), which functioned as a third team member. Students prompted the AI to contribute to discussion, support problem-solving, and assist in the co-creation of instructional materials. This design enabled integration of individual self-report measures with experiential accounts of human–AI teamwork.

3.2. Participants

Participants were 150 undergraduate students (75 dyads) enrolled in an education program at a Vietnamese university. All participants had prior exposure to basic AI tools but limited experience collaborating with generative AI in problem-solving contexts. From the full sample, a purposive subsample of 33 students participated in post-task semi-structured interviews. Participation was voluntary, informed consent was obtained, and all personal data were anonymized. Participants were informed that all interaction data, including AI-generated responses, would be used solely for research purposes. The study adhered to institutional ethical guidelines.

3.3. Procedure

Data collection followed a structured sequence consisting of a pre-task survey, two collaborative tasks, an interval survey, a post-task questionnaire, and post-task interviews. First, all participants completed an online pre-task survey assessing baseline levels of technostress, general stress, and anticipatory stress associated with AI use. Immediately after completing the survey, participants engaged in Task 1, during which they worked in pairs with Gemini for 20 minutes to discuss the prompt: "Should primary school students be allowed to use AI? Why or why not?" Students who supported AI use proposed meaningful AI-based learning activities for young learners, whereas those who disagreed designed activities promoting appropriate and responsible AI use. After the completion of Task 1, participants filled out a brief interval survey capturing immediate stress levels and initial perceptions of the collaborative experience with AI. They then proceeded to Task 2, a 30-minute design activity in which pairs jointly developed a pedagogically oriented learning activity plan based on their consensus from Task 1. The outcomes were presented using a slideshow format (e.g., PowerPoint, infographics, or Canva). Participants were free to use any sources, search tools, or AI systems they found appropriate. All verbal exchanges, on-screen interactions, and AI-generated contributions were recorded to capture the full dynamics of human–AI–human collaboration. Following the completion of Task 2, participants responded to a post-task questionnaire examining perceived technostress, cognitive load, task complexity, and evaluations of team collaboration. Finally, a purposive subsample of 33 students participated in 30–45 minute semi-structured interviews exploring emotional, cognitive, and collaborative experiences with Gemini, with a particular focus on perceived technostress and the interactional dynamics of human–AI teams.

3.4. Instruments

Baseline technostress was measured using a standardized instrument [21], assessing dimensions such as techno-overload, techno-complexity, techno-uncertainty, and anticipatory stress. Items were rated on a Likert scale and slightly reworded to align with AI-supported learning contexts. Post-task experiences were explored through semi-structured interviews adapted from [22]. The protocol examined perceived technostressors, the role of AI in shaping cognitive and emotional strain, and coping strategies used

Table 1
Descriptive Statistics for Pre-Task Technostress Dimensions (N = 150)

Technostress Dimension	M	SD	Min	Max
Techno-Overload	3.26	0.83	1.00	5.00
Techno-Invasion	3.07	0.83	1.00	5.00
Techno-Complexity	3.38	0.80	1.00	5.00
Techno-Insecurity	3.53	0.82	1.00	5.00
Techno-Uncertainty	3.12	0.80	1.00	5.00

Note. Higher scores indicate greater technostress.

Table 2
Paired-Samples t-Tests Comparing Technostress Dimensions (N = 150)

Comparison	MD	SD_{diff}	$t(149)$	p	d
Techno-Overload vs. Techno-Invasion	0.19	0.55	4.09	$< .001$	0.33
Techno-Overload vs. Techno-Complexity	-0.12	0.78	-1.88	.062	-0.15
Techno-Overload vs. Techno-Insecurity	-0.27	0.87	-3.86	$< .001$	-0.32
Techno-Overload vs. Techno-Uncertainty	0.13	0.77	2.08	.040	0.17
Techno-Invasion vs. Techno-Complexity	-0.31	0.68	-5.53	$< .001$	-0.45
Techno-Invasion vs. Techno-Insecurity	-0.46	0.77	-7.29	$< .001$	-0.60
Techno-Invasion vs. Techno-Uncertainty	-0.05	0.74	-0.90	.370	-0.07
Techno-Complexity vs. Techno-Insecurity	-0.15	0.65	-2.89	.004	-0.24
Techno-Complexity vs. Techno-Uncertainty	0.25	0.65	4.76	$< .001$	0.39
Techno-Insecurity vs. Techno-Uncertainty	0.40	0.69	7.18	$< .001$	0.59

during collaboration with both human partners and AI systems. Together, these instruments provided complementary quantitative and qualitative insights into technostress in human–AI teams.

4. Preliminary Results

4.1. RQ1. Baseline Levels of Technostress

Students reported moderate to high levels of technostress prior to the human–AI collaborative task. As shown in Table 1, Techno-Insecurity and Techno-Complexity showed the highest mean levels, followed by Techno-Overload, Techno-Uncertainty, and Techno-Invasion. These results indicate that students entered the task with notable concerns about keeping up with AI developments, understanding AI tools, and managing increased cognitive demands.

Paired-samples t-tests (Table 2) revealed significant differences between several technostress dimensions. Techno-Insecurity was significantly higher than Techno-Overload, Techno-Invasion, and Techno-Complexity. Differences between Techno-Overload and Techno-Complexity and between Techno-Invasion and Techno-Uncertainty were not statistically significant. Overall, insecurity and complexity emerged as the most salient baseline stressors.

As shown in Table 2, several significant differences emerged between technostress dimensions. Techno-Insecurity demonstrated the largest discrepancies across comparisons, with medium effect sizes (e.g., $d = 0.59$ for Insecurity vs. Uncertainty; $d = -0.60$ for Invasion vs. Insecurity), indicating that insecurity-related stress was experienced more intensely than other forms of technostress. Techno-Complexity also differed significantly from Techno-Invasion and Techno-Uncertainty, each with small-to-medium effects, suggesting that cognitive challenges associated with understanding and using generative AI tools were comparatively salient. By contrast, differences involving Techno-Invasion and Techno-Uncertainty were small and non-significant, reflecting similar levels of perceived intrusion and ambiguity. Collectively, these results indicate that feelings of insecurity and complexity were the most distinctive and elevated stressors prior to the human-AI collaborative task.

4.2. RQ2. Technostressors During Collaboration

Preliminary qualitative analysis indicated that students encountered several technostressors while engaging in the human–AI collaborative task. Learners frequently described interpretive uncertainty, particularly difficulty in assessing the correctness, clarity, and usefulness of AI-generated responses. They also reported cognitive overload when monitoring, verifying, and integrating multiple information streams, as well as role ambiguity when coordinating decision-making between themselves, their partner, and the AI system. Some students additionally expressed frustration when Gemini produced unpredictable or unhelpful outputs. These preliminary findings align with existing literature indicating that AI opacity, cognitive demands, and unpredictability are common sources of technostress in educational and workplace settings. However, the current study will examine these dynamics in greater depth as qualitative coding progresses.

4.3. RQ3. Coping Mechanisms and Adaptive Strategies

Students described a range of strategies used to regulate technostress during the collaborative task. These included interpretive coping strategies, such as refining prompts and cross-checking AI outputs; collaborative coping strategies, including dividing responsibilities for AI interaction and synthesis; and emotion-regulation strategies, such as temporarily reducing reliance on the AI or renegotiating roles to manage frustration. These coping responses are consistent with prior research highlighting learners' active attempts to regain control when working with complex AI systems. Ongoing analysis will further examine how these strategies function within human–AI teams and the conditions under which they support or hinder effective collaboration.

5. Discussion and Conclusion

The aim of this study was to examine how technostress emerges and is managed in human–AI teams within collaborative learning settings. Although analyses are ongoing, the study is expected to advance empirical understanding of technostress in higher education Hybrid Intelligence (HI) contexts across three key areas. First, the study provides an initial characterization of technostress levels and dimensions in human–AI teams. Given that technostress is highly context-dependent and task-specific [8], situating the investigation within an educational teamwork context offers an important extension to existing literature. Second, the study examines technostress within authentic collaborative tasks, a dimension that remains underexplored [8]. Prior research has shown that AI complexity (e.g., interpretive difficulty and unpredictability) and uncertainty (e.g., unstable behavior and constant updates) are core stressors in AI-rich environments [7]. Emerging research further identifies malfunction, misjudgment, and technical instability as key triggers of techno-overload, techno-complexity, and techno-uncertainty [19]. These insights align with expectations that ambiguity, correctness doubts, and interpretive effort are central stressors in human–AI team-based reasoning tasks. Emotional disconnection and responsibility ambiguity further suggest that interpersonal tensions may arise as learners negotiate roles and accountability with an AI teammate. Evidence from educational AI contexts supports this perspective, showing that learners often experience uncertainty and discomfort when AI feedback is opaque, unpredictable, or difficult to trust [23].

Third, the study is expected to contribute an empirically informed account of how learners cope with technostress during AI-integrated teamwork. Anticipated findings include insights into how techno-overload, techno-uncertainty, and techno-complexity are experienced and regulated during shared problem-solving, as well as the emergence of coping strategies adapted to AI-supported interaction, such as interpretive regulation, accuracy-checking, and emotional management. These responses, including frustration and increased cognitive effort, reflect known challenges in working with AI systems and highlight the importance of coping mechanisms in navigating AI-related uncertainty [23]. The study is positioned to clarify how technostress manifests when AI functions as a collaborative teammate, addressing a key gap in human–AI teaming research [11, 12]. It contributes to refining conceptual understandings of technostress by incorporating interpersonal coordination, cognitive labor distribution, and AI unpredictability. Methodologically, the study advances the field through its integration of pre-task surveys, AI-supported collaborative tasks, and post-task interviews, addressing the overreliance on single-source self-report methods [6]. Additionally, by operationalizing AI as a third team member within authentic academic tasks [10], the study provides a replicable design for future research. Collectively, these contributions lay the groundwork for empirical investigations into technostress in human–AI teams and inform the development of psychologically supportive HI learning environments in higher education.

Following these preliminary analyses, the next phase of this research will involve completing comprehensive qualitative coding of all interview and interaction data to more precisely characterize technostressors and coping processes within triadic human–AI collaboration. This will be followed by an integrative mixed-methods phase, in which quantitative technostress profiles are systematically linked with qualitative findings to examine how baseline stress dispositions shape learners' experiences. Further analysis of interaction data will capture micro-level regulatory and sense-making processes through which technostress unfolds in real time, supporting the development of an empirically grounded conceptual model of technostress in Hybrid Intelligence teams. These insights will inform theoretical, methodological, and practical implications, including design-oriented recommendations for developing AI-supported learning environments that minimize cognitive strain and support effective human–AI collaboration.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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