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Moods, bots, and bodies: University students' emotional and physiological responses to human vs. GenAI chatbots

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Abstract

As generative AI (GenAI) chatbots become more common as learning partners, questions remain about students' emotional and physiological responses to them. A multimodal design was used to compare university students' experiences during a 25-minute brainstorming session with either a human teacher or GenAI chatbot. 30 participants wore EmbracePlus sensors to record heart rate, electrodermal activity, and skin temperature while completing the task, and completed mood questionnaires before and after brainstorming. Analyses compared mood change scores and examined physiological data for both temporal patterns and total activation (area-under-the-curve; AUC). Although both groups reported increases in several positive moods, outcome-specific differences emerged, whereby students brainstorming with a human teacher showed greater gains in positive mood, whereas the chatbot group reported increased stress and discouragement. Although physiological change trajectories did not differ by condition, condition differences emerged for selected physiological indicators, and specific AUC measures were associated with mood outcomes: higher pulse AUC was linked to negative moods, and higher skin temperature AUC to positive moods. These findings provide preliminary evidence that human facilitation may produce stronger positive emotional outcomes, while GenAI chatbots can support meaningful physiological engagement and may serve as valuable complementary learning tools. Physiological signals also revealed associations between bodily states and emotional experiences, underscoring the value of integrating multimodal data into research on AI-mediated education.

Introduction

As the education landscape rapidly evolves with the integration of generative AI (GenAI), opportunities and challenges abound, particularly in its potential to transform traditional teaching methods. There is now a sharp rise in AI-based education applications; for example, educational games, adaptive learning platforms, AI chatbots serving as virtual teaching assistants, personalised tutors, and interactive learning companions across diverse education levels all over the world. AI systems can personalise learning content and experience to match one's pace, needs and abilities regardless of time or geography, and provide feedback (e.g., Labadze et al., 2023), making it increasingly accessible and personalised.

Emerging research underscores the potential of GenAI tools in language and literacy education. Chandel and Lim (2025), in a systematic review of empirical studies, examine how GenAI applications such as AI-powered writing assistants and conversational chatbots are being integrated into classroom practice to support literacy development across reading, writing, and multimodal meaning-making. The review highlights the affordances of GenAI in facilitating ideation and planning, with studies like Mahapatra (2024) demonstrating the benefits of such tools in supporting learners during the brainstorming phase of writing. However, there is limited literature on students' receptivity to using GenAI for learning or help-seeking compared to human educators, especially when explored through experimental methods rather than interviews. For instance, a recent mixed-method study of 687 university students found that perceived usefulness significantly shaped students' attitudes and intentions to use ChatGPT for academic tasks, with many students reporting benefits like time savings and enhanced creativity. However, students also expressed concerns relating to over-reliance, mistrust of generated content and risks to academic integrity (Stroud & Du, 2025).

While AI offers a multitude of advantages, aspects unique to GenAI can potentially impede learning. For example, in a study consisting of students learning a second language through virtual human interactions, students' levels of frustration were modulated by factors such as "not being understood or heard as expected" (Ericsson et al., 2023). This is a common trend when engaging with AI, where nuanced human dynamics are missing. Other features of GenAI, such as perceived warmth and emotional responsiveness, have been shown to affect individuals' attitudes towards having AI as a teammate (Harris-Watson et al., 2023). Specifically, perceived warmth and competence positively predict individuals' receptivity to AI in three aspects, including their willingness to adapt routines, integrate AI's expertise and skills and regard AI as a valued teammate. Even though individuals may appreciate the efficiency or flexibility of AI systems, the absence of "human" qualities like empathy, adaptability, encouragement, personal connection and trustworthiness in AI bots can affect their satisfaction levels and how willing they are to engage and rely on them for knowledge building (e.g., Cevher & Yıldırım, 2023; Demeure et al., 2011).

Given the established link between emotional arousal, attention and learning effectiveness (Loderer et al., 2020), along with the increasing integration of AI in education, it is crucial to deepen our understanding of how students perceive and interact with GenAI compared to human educators. Although the educational potential of GenAI is often evaluated through performance outcomes, learning is fundamentally an emotional and embodied experience. Emotional states influence learners' engagement, persistence, and responses to challenge, while physiological responses provide insight into aspects of experience that may not be fully captured through self-report measures. Emotional engagement in learning involves interconnected affective, cognitive, and physiological processes, and physiological indicators such as heart rate, electrodermal activity, and skin temperature have been increasingly used as complementary measures of arousal, attentional engagement, and affective responding during learning activities (for a review, see Horvers et al., 2021). Examining self-reported mood alongside physiological responses may provide a more comprehensive understanding of how learners experience interaction with human versus AI-supported educational partners. Such insights can inform the development of blended learning environments that optimise the strengths of both AI and human educators, ensuring that AI serves as a pedagogical aide for the teacher.

To address the limited research comparing emotional and physiological responses to human- versus AI-facilitated brainstorming, the present study was designed as an exploratory proof-of-concept investigation. This study investigates how students' emotional and physiological responses differ when brainstorming with a GenAI chatbot versus a human teacher. We focus on self-rated mood and physiological arousal as complementary indicators of learners' affective and embodied engagement during collaborative brainstorming, aiming to better understand how learners experience human- and GenAI-facilitated brainstorming and how these experiences may inform the design of AI-supported learning environments. Specifically, we examine motivational and engagement-related positive moods (e.g., motivated, inspired, engaged), affective and social experiences (e.g., excitement, connectedness), and task-related negative moods (e.g., stress, boredom, frustration), which prior work suggests are closely implicated in learning-relevant processes in collaborative and generative tasks (e.g., Pekrun et al., 2002; Plass & Kaplan, 2016). The study addresses three questions: 1) How do students' emotional responses differ between chatbot- and human-facilitated brainstorming? 2) How do students' physiological responses differ between chatbot- and human-facilitated brainstorming? 3) How are students' physiological signals related to their self-reported moods, regardless of condition?

Literature review

Brainstorming and facilitation for writing

Brainstorming is widely recognised as an effective pre-writing strategy that enhances idea generation, organisation, and refinement, leading to higher-quality essays with greater originality and depth (Crossley et al., 2016). In externalising their thoughts during brainstorming, writers engage in metacognitive reflection, structuring ideas more clearly, drawing on prior knowledge, considering various perspectives, and approaching writing more fluently (Kellogg, 1990; O'Mealia, 2011). Structured planning before essay writing has been shown to improve clarity and overall quality in students (Nugraha & Indihadi, 2019).

Brainstorming is especially valuable for students who struggle with idea expression, confidence, lexical retrieval, or adherence to academic writing conventions (Abedianpour & Omidvari, 2018). For example, for English as a foreign language (EFL) learners, brainstorming provides cognitive and linguistic scaffolding as well as emotional support, helping to reduce writing anxiety, build confidence, and strengthen their ability to generate, organise and articulate ideas more effectively (Unin, 2016).

The cognitive and emotional benefits of brainstorming can be further amplified in collaborative settings, where social interaction, peer feedback and co-construction of meaning help students engage more actively with their ideas to revise their thinking in real time. Ideation with others encourages critical thinking, creativity, and the exchange of alternative perspectives, helping students to build richer and more multidimensional ideas (Al-Khatib, 2012; Ghabanchi & Behrooznia, 2014). However, human-facilitated brainstorming may not always be accessible. Increasingly, GenAI is filling this gap, offering personalised, on-demand brainstorming chatbots that can simulate aspects of effective human-led support. These systems can be designed to possess in-depth domain knowledge, ask probing questions, and respond adaptively to student input. Critically, they also offer a "judgment-free" space – an important feature for students who may hesitate to seek help due to fear of negative evaluation (Ryan et al., 1998). By lowering social barriers, such chatbots reduce anxiety, encourage intellectual risk-taking, and promote deeper inquiry and self-regulated learning (Zimmerman, 2002).

Chatbots in educational support

Recent studies illustrate both the potential and complexity of chatbot-facilitated brainstorming. In a quasi-experimental study, Zhang et al. (2025) found that students using an AI chatbot (Spark Desk) during argumentative writing showed significant gains in critical thinking skills and intrinsic motivation, including higher enjoyment, greater perceived value of the task and reduced stress, as compared to peers engaged in peer interaction. Similarly, Guo and Li (2024) showed that students, who built their own chatbots for idea generation, outlining and language correction, developed clearer goals, greater writing confidence, and more positive attitudes toward writing. These chatbots also handled diverse requests, including "assistance, customisation, and translation", which would have been overwhelming for a single human teacher to address for multiple students.

Still, chatbot-led ideation has drawbacks. AI-generated brainstorming can be less diverse, with high overlap across responses, compared to human brainstorming (Meincke et al., 2025). Educators also express reservations: Karanjakwut and Charunsri (2025) found that while Thai university students using AI chatbot tools outperformed a control group on several assignments, lecturers still preferred student-generated ideas over chatbot suggestions. Meta-analytic evidence provides a more balanced view – Wang and Fan's (2025) review of 51 studies concluded that ChatGPT use has a large positive impact on learning performance, and a moderately positive effect on higher-order thinking and perceived learning.

Together, these studies suggest that, when thoughtfully integrated, chatbots can serve as flexible, personalised brainstorming partners, and that their influence on students' engagement and confidence may differ from that of human teachers. Yet most existing work has focused narrowly on linguistic outcomes, without examining students' emotional responses, let alone making comparisons to experiences with human teachers (Jeon & Lee, 2024). This study addresses that gap by examining learners' emotional and physiological responses to explore how human and AI tools shape the brainstorming experience.

Emotion and learning

"Emotion is the foundation of learning" (Zull, 2006, p. 7). Traditionally viewed as a cognitive process, learning is now widely recognised as deeply influenced by motivation and emotional processes, including what is learned and retained (Plass & Kaplan, 2016). Emotions direct attention, motivation and affect memory (Mayer, 2020), and are integral to the causal chain leading to learning outcomes, particularly in digital environments. Learning results not only from instructional design and content, but also from learners' emotional responses to the process. Emotions, short-lived, intense reactions to specific events or stimuli, can either facilitate or hinder learning, depending on their nature and timing (Duffy et al., 2020). Understanding how learners feel is therefore critical for designing more effective learning experiences (Boekaerts, 2010).

Empirical studies support the influence of specific emotional states on cognitive performance. Emotional content is remembered more clearly than neutral content, as emotional experiences engage both the amygdala and hippocampus during memory formation, enhancing the consolidation of emotionally significant information and leading to stronger long-term recall (Tyng et al., 2017). Positive emotions like enjoyment, pride and enthusiasm are strong drivers of learning motivation, academic performance (Pekrun et al., 2002), self-regulation, cognitive flexibility and problem solving (Li et al., 2020). However, not all emotions affect learning in the same way. For example, stress can either support or hinder learning depending on its intensity and duration (Vogel & Schwabe, 2016). Mild, acute stress may enhance attention and memory, while chronic or excessive stress tends to impair cognitive performance.

Importantly, not only positive emotions contribute to effective learning. Certain negative states, like confusion, can improve learning outcomes by increasing focus on the learning content (D'Mello et al., 2014). Positive emotions like curiosity promote exploration and prepare the brain for learning and material retention in both children and adults (Oudeyer et al., 2016). In collaborative learning contexts, these learning-relevant emotional mechanisms are often reflected in learners' motivational and engagement-related states, affective and social experiences. Together, these studies demonstrate that both positive and negative emotional experiences can facilitate learning under the right conditions, highlighting the importance of how emotional states influence attention, engagement and memory in educational contexts.

AI support for emotional engagement in learning

Given that learning is not merely a cognitive process but also about how learners feel, react and regulate during the process, as educational research increasingly recognises the role of emotion in shaping attention, motivation and memory, there is growing interest in how AI-based systems can support not just what students learn, but how they experience learning emotionally.

Recent advances in emotion detection technologies have enabled AI tools to predict and identify emotions that impede learning, such as boredom and frustration, by analysing cues in their chatlogs or interaction patterns. Adap-

-tive systems can then respond to students' emotions and behaviour dynamically to increase motivation and productivity (Arguel et al., 2019; Mehigan & Pitt, 2019). For example, Sumithra and colleagues (2022) demonstrated how, by using emotion-detection algorithms, AI systems can adapt lesson content and pace to match students' emotional intensity and attention levels, while ensuring timely completion. In this sense, AI chatbots can mirror a human tutor's responsiveness to individual students, while remaining consistent, unbiased and available on demand. Emerging models can even simulate social-emotional intelligence (Gorga & Schneider, 2009), thus providing more responsive, emotionally supportive digital learning environments that begin to approximate some aspects of the emotional responsiveness traditionally associated with human teachers, such as empathy, adaptability and relational support. As GenAI tools become more emotionally intelligent, integrating physiological data offers a promising next step – providing real-time, complementary insight into learners' emotional states.

Embodiment and the physiological measurement of emotion

Emotions are rooted in the body as much as the mind, involving complex interactions between physiological and neural processes. Theories of interoception and embodied cognition suggest that emotions are shaped not only by subjective interpretations, but also by the perception and regulation of internal bodily states (Barrett & Simmons, 2015). Relatedly, emotions reflect the body's efforts to maintain homeostasis – its internal equilibrium. This balance is disrupted in times of stress or discomfort, and individuals at these moments, tend to experience negative emotional states. Contrastingly, restoring this balance is linked to positive feelings such as calmness (Craig, 2002).

In educational settings, positive emotional states like interest, curiosity and focus support deeper cognitive processing and sustained attention (Tyng et al., 2017). While these experiences are often reported subjectively, they also have physiological signatures, such as changes in skin temperature, heart rate, and electrodermal activity (EDA) (Malmberg et al., 2019), which reflect shifts in arousal, attention, and emotional reactivity.

However, while self-report questionnaires remain useful for assessing learning and emotion, they are subject to biases (e.g., social desirability, limited recall, lack of awareness), and do not capture moment-to-moment or subconscious changes in emotional state (Pekrun, 2020). To address these challenges, researchers increasingly adopt multimodal techniques that combine self-reports with objective indicators of emotional arousal and engagement, including classroom observations, eye-tracking, learning analytics, and physiological signals (e.g., Ketonen et al., 2023). EDA, commonly used in studies assessing student engagement (Horvers et al., 2021), tracks changes in skin conductance driven by the sympathetic nervous system and is sensitive to shifts in emotional intensity and attention (Boucsein, 2011). Heart rate provides insight into emotional valence and cognitive effort; higher heart rate, for instance, is associated with increased cognitive workload (Darnell & Krieg, 2019). Skin temperature typically drops during sympathetic activation (e.g., anxiety) due to vasoconstriction, and rises during relaxed or regulated states (Gouizi et al., 2011). Because physiological data and self-report tap into different aspects of experience, they do not always align. Self-reports tend to offer summarised or retrospective accounts of how learners felt, whereas physiological data capture the immediate and embodied dimensions of emotional responses that may be fleeting, subtle or subconscious (e.g., Ketonen et al., 2023).

Capturing the embodied dimensions of emotional dynamics allows researchers to move beyond what learners say they feel, to observe how their bodies respond to specific instructional events (Harley, 2016). This is especially useful when comparing interactions with human instructors versus GenAI systems, where differences in emotional and cognitive engagement may not be fully verbalised but can still be detected physiologically.

Taken together, these strands of research suggest that learners' engagement during collaborative brainstorming emerges through interacting emotional, cognitive, social, and physiological processes. In AI-mediated learning contexts, these processes may be reflected both in subjective (self-reported) emotional experiences and in physiological indicators associated with arousal, attentional engagement, and emotional regulation. Accordingly, this study adopts a multimodal perspective on learner engagement, examining how interactions with a human teacher versus a GenAI chatbot shape both subjective mood states and embodied physiological responses during collaborative brainstorming. Figure 1 presents the conceptual framework guiding the study. The framework proposes that interactions with either a human teacher or a GenAI chatbot shape learners' emotional and cognitive experiences during brainstorming, which are reflected in both subjective mood reports and physiological indicators of arousal, engagement, and emotional regulation. Examining these complementary indicators provides a multimodal perspective on learner engagement.

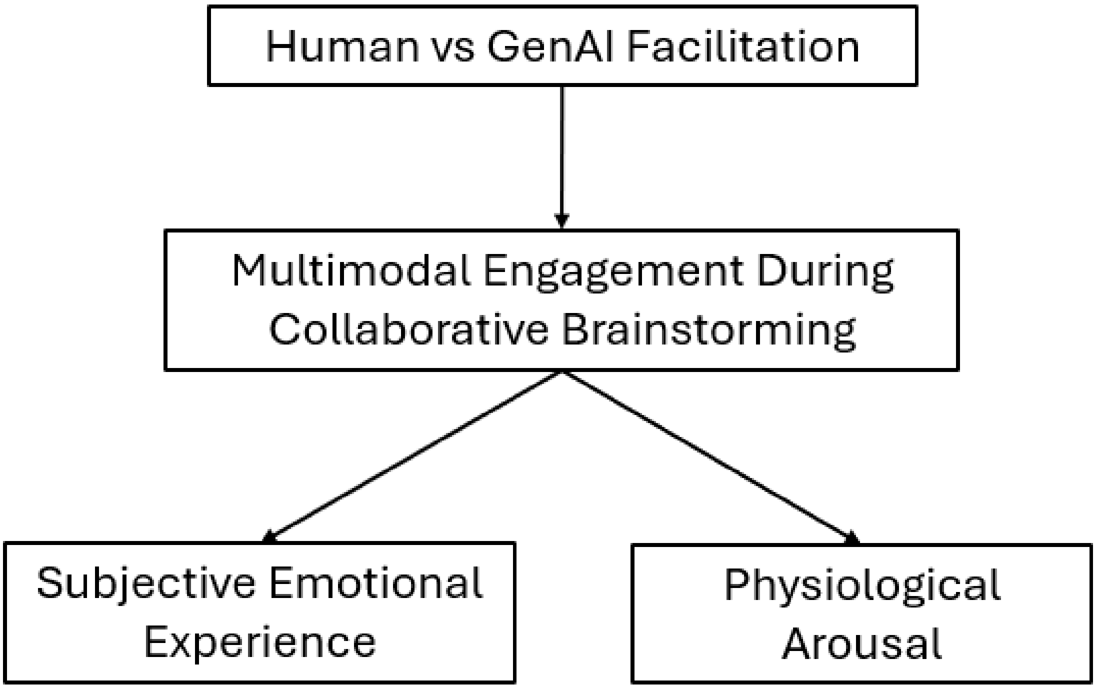

Figure 1. Conceptual framework of multimodal engagement during AI-mediated collaborative brainstorming, reflected through subjective emotional experiences and physiological arousal.

Informed by the literature review, we propose the following hypotheses guiding our study. The first is that learners who engage in brainstorming with a GenAI chatbot will report similar levels of positive emotional states (e.g., curiosity, enjoyment, confidence, and perceived psychological safety) to learners who engage in brainstorming with a human teacher. This is because GenAI chatbots provide personalised, on-demand, and judgement-free support, which may reduce evaluation anxiety and encourage intellectual risk-taking, even as we recognise that engagement with a human teacher will still be inherently emotionally satisfying. The second is that learners who engage in brainstorming with a GenAI chatbot will report significantly lower levels of negative emotional states (e.g., anxiety, stress, and apprehension) than learners who engage in brainstorming with a human teacher. This is due to the absence of perceived social evaluation, which may reduce emotional barriers during idea generation. Finally, learners who engage in brainstorming with a GenAI chatbot will exhibit physiological patterns indicative of similar emotional regulation and lower stress compared with learners who engage in brainstorming with a human teacher. This could be attributed to the fact that lower sympathetic nervous system activation is generally associated with reduced stress and greater emotional comfort.

Methods

The protocol was approved by Nanyang Technological University’s Institutional Review Board (IRB-2024-1031) in accordance with all relevant laws, regulations, and institutional guidelines. This study employed a multimodal design to investigate learners’ experiences with AI- versus human-facilitated brainstorming during an essay planning task. Participants first completed a pre-task mood questionnaire, then engaged in a 25-minute brainstor-

-ming session with either a human or chatbot facilitator. Immediately afterwards, they completed a post-task mood questionnaire and wrote an essay outline. Throughout the brainstorming phase, continuous physiolog-gical signals were recorded using a wearable sensor, enabling the assessment of not only how learners *report* feelings, but also how their bodies respond, thus offering an alternative perspective into the embodied dimensions of human-AI interaction.

The essay outline writing activity served two primary purposes. Firstly, it provided a concrete context and goal, helping to anchor participants' sense of purpose and engagement during the brainstorming process. Secondly, it offered an objective behavioural outcome measure of brainstorming effectiveness of each facilitation condition. However, because this paper focuses on emotional and physiological responses, analyses of writing performance fall outside the current scope and will be reported separately.

We recruited 30 undergraduates and postgraduates, as they are likely to engage in learning activities with both AI and the human facilitator. Participants were allocated to one of two conditions using an alternating assignment procedure based on order of recruitment, resulting in balanced group sizes across the chatbot (n = 15; 11 female; *M* age = 28.6, *SD* = 6.92) and human teacher conditions (n = 15; 11 female; *M* age = 29.2, *SD* = 5.15). Participants in the chatbot condition brainstormed ideas with the assistance of a customised messaging chatbot, while participants in the human condition engaged in the same brainstorming task with the help of a human teacher via the chat function on Zoom, without the audio and video features turned on. The identities of the participants in the human teacher condition were not revealed to the human teacher and vice versa.

The brainstorming task centred on the essay question, "Should Singapore embrace Singlish as a key part of its national identity, or does it undermine its global image?" Participants were instructed to develop an outline for an argumentative essay in response to this prompt after the brainstorming session. The essay outlines were then graded according to a rubric developed.

The GenAI chatbot used in the study was developed using the SchoolAI platform (app.schoolai.com), which enables the customisation of chatbots using tailored prompts and supplementary materials. For this study, the chatbot's knowledge base was augmented with selected readings on Singapore English and Singlish. Unlike typical chatbots that serve to provide direct and complete answers, the design strategy adopted for our chatbot followed a Socratic questioning approach – posing reflective, open-ended questions to encourage critical thinking and avoiding giving participants direct answers. The specific system prompts used can be found in Supplementary Material 1.

The human teacher engaged in the study is a lecturer in a reputable university in Singapore with teaching experience in Academic Writing, Professional Communication, Linguistics and English Language across various tertiary institutions. Their academic specialisation includes English in Singapore, providing a strong match to the chatbot's domain expertise.

Before brainstorming, participants completed a baseline mood questionnaire and a 5-minute control condition viewing a neutral video (https://www.youtube.com/watch?v=zpHOIlQbj8Y) to elicit a stable, low-arousal state. Visual exposure to natural environments has consistently been associated with physiological relaxation and reduced sympathetic activation across a range of laboratory studies (for a review, see Jo et al., 2019). Physiological effects have been observed following exposures as brief as 60–90 seconds, including reductions in prefrontal cortical activation and sympathetic nervous system activity. A five-minute viewing period was therefore selected to provide participants with sufficient time to settle into a relatively stable physiological state before brainstorming commenced. The resulting measures served as emotional and physiological baselines, accounting for individual differences in resting states and enabling more accurate condition comparisons. Participants were explicitly informed in advance whether they would be interacting with a chatbot or a human teacher to mimic real-world learning scenarios, where individuals are typically aware of the nature of their learning facilitators. By doing so, we aimed to enhance the ecological validity of the study as it reflects more accurately the variety of help-seeking behaviours and communication experiences participants may encounter outside the study setting, while avoiding introducing confusion or expectancy effects during the task. In particular, since it is highly plausible that participants in the chatbot condition might infer the identity of the conversational partner over time, we sought to prevent any potential disruptions in emotional or physiological responses caused by such realisations.

Following the brainstorming phase, participants completed a follow-up questionnaire containing the same mood items found in the pre-brainstorming questionnaire, as well as an additional 15 questions on perceptions of the brainstorming interaction. These self-reported measures not only allowed for direct comparison to their baseline mood, but also served to contextualise and supplement the physiological data, providing a more comprehensive view and nuanced analysis of the impact of the two experimental conditions (AI vs human).

The mood questionnaire contained 20 items (10 positive, 10 negative; e.g., excited, stressed, frustrated) with the intensity of each rated on a 5-point Likert scale from "None" to "Very intense". These ratings were used to assess mood change over time and compare emotional outcomes across the conditions (human vs chatbot). The second questionnaire's additional 15 perception questions covered aspects such as effectiveness and ease of communication. See Supplementary Material 2 for the full list of items.

Physiological responses were collected using the EmbracePlus wearable sensor, which records continuous, real-time, non-invasive biomarkers relevant to emotional and cognitive engagement. Specifically, we measured heart rate, EDA, and skin temperature. These measures were selected based on prior research linking them as proxies for affective arousal, attentional focus, and engagement in learning contexts (Fang et al., 2018; Soltis et al., 2020).

Data analyses

All analyses were conducted in R (version 4.3.1; R Core Team, 2025) using descriptive statistics, MANCOVA, regression, and mixed-effects models to examine physiological and emotional responses during the brainstorming task. Analyses addressed: (1) group differences between the Chatbot and Human teacher conditions, and (2) associations between physiological activation and mood outcomes. Consistent with the study's proof-of-concept and exploratory design, the analyses focused on identifying preliminary patterns of emotional and physiological engagement associated with human versus GenAI facilitation.

Mood analyses

Mean mood ratings were first compared descriptively at baseline and brainstorming phases. However, analysing raw mood ratings at each phase separately risks misinterpretation. For instance, a higher brainstorming phase mood rating in the human condition does not necessarily mean the chatbot group showed no improvement; it simply reflects an endpoint comparison without accounting for each participant's baseline.

To more accurately capture emotional shifts, mood change scores were computed for each item by subtracting the baseline rating from the brainstorming rating (Brainstorming – Baseline). Positive change scores indicate increased mood intensity during brainstorming (Brainstorm > Baseline) while negative scores reflect decreases (Brainstorming < Baseline). Change scores were used to capture within-participant emotional shifts across the brainstorming task while accounting for baseline mood variability in a parsimonious manner more appropriate for the study's sample size.

Change scores were entered into a MANCOVA to assess overall condition effects, controlling for gender and age. Age and gender were included as covariates because previous research has shown that demographic characteristics may influence emotional regulation and physiological activity (Koenig & Thayer, 2016; Sanchis-Sanchis et al., 2020). Although the groups did not significantly differ in age or gender composition, these variables were retained as precautionary controls to account for potential individual differences unrelated to experimental condition. Follow-up univariate ANCOVAs for individual mood dimensions were conducted using Type III sums of squares. For each outcome, regression coefficients, standard errors and estimated marginal means were extracted from the corresponding covariate-adjusted linear model to aid interpretation of the direction and magnitude of condition effects.

Physiological analyses

Physiological data (heart rate, EDA, temperature) were analysed separately for the baseline (5 min; 5 data points) and brainstorming (25 min; 25 data points) phases. For each phase, two types of metrics were used: raw means and Area Under the Curve (AUC) values. AUCs were calculated using the trapezoidal method to capture sustained physiological engagement across each phase (5-min baseline, 25-min brainstorming). AUC provides an index of cu-

-mulative physiological activation over time and is useful for summarising prolonged states such as engagement, arousal and stress. One participant contributed only 4 baseline data points, and thus their baseline AUC could not be computed. This participant was excluded from analyses involving baseline AUC.

All physiological measures (raw means and AUCs) were analysed using the same statistical approach. For the baseline phase, MANCOVAs compared groups (chatbot vs human) with age and gender as covariates. For the brainstorming phase, MANCOVAs tested condition differences while controlling for all baseline measures, age and gender. This approach allowed the examination of condition differences in the overall physiological profile during brainstorming while accounting for pre-existing individual differences in physiological activity. Baseline physiological measures were included as covariates because physiological responses can vary considerably across individuals and may influence subsequent task-related measures (e.g., Levenson, 1994). Controlling for baseline levels, therefore, helps isolate task-related variation from pre-existing physiological differences between participants. Follow-up univariate ANCOVAs were conducted using Type III sums of squares from the corresponding covariate-adjusted linear models. Covariate-adjusted estimated marginal means and 95% confidence intervals were extracted to aid interpretation of the direction and magnitude of effects.

To analyse minute-by-minute trajectories of physiological change during brainstorming, linear mixed-effects models (using the lmer function in R) were fitted. This approach was chosen because it accommodates repeated measures data, allowing us to model both between-subject differences and within-subject changes over time. The models included fixed effects for Time, Condition and their interaction, as well as random intercepts by participant to account for individual variability (e.g., each participant may have inherently different physiological levels at baseline). The random effects' structure was constructed following the recommendations of Bates et al. (2015), prioritising an accurate reflection of the experimental design while also maintaining model parsimony. This growth curve modelling approach allowed us to assess whether the trajectories of physiological responses differed by condition across the 25-minute brainstorming session.

Integration of mood and physiological data

To explore the relationship between physiological responses and mood changes, independent of experimental condition, multiple regression analyses were conducted examining relationships between physiological AUC values and mood change scores (both composite positive/negative mood scores and individual mood items). This approach assessed the associations between physiological responses and subjective mood experiences, regardless of condition. Because prior work integrating physiological and subjective indicators in AI-mediated brainstorming contexts remains limited, these analyses were intended to identify preliminary patterns of association rather than establish confirmatory predictive models.

For the regression analyses, assumptions were assessed through visual inspection of residual, Q-Q, scale-location, and leverage plots. Normality and homoscedasticity were further examined using Shapiro-Wilk and Breusch-Pagan tests, respectively. Variance inflation factors were used to assess multicollinearity.

Findings

Mood

Descriptive statistics

At baseline, participants in the chatbot condition reported higher levels of positive emotions, while those in the human condition reported higher levels of negative emotions. However, this pattern reversed post-brainstorming: chatbot participants experienced more intense negative moods, whereas the human condition saw greater increases in positive emotions.

Descriptive statistics and mood change scores (brainstorm – baseline) are presented in Supplementary Table S3.1. Both groups showed increases in positive moods, 7 of 10 moods, with larger gains in the human teacher group. Th-

-ree positive moods saw chatbot-only decreases – Curious, Motivated and Excited. The chatbot group also showed increases in negative moods, particularly Stress, Discouragement, Boredom and Distraction.

Inferential statistics for baseline mood and mood change scores

At baseline, a MANCOVA controlling for gender and age revealed no significant multivariate effect of Condition (Pillai's Trace = 0.60, *F*(20, 6) = 0.45, *p* = 0.92), indicating that both groups began the brainstorming session with comparable mood states. For mood change scores (Brainstorming mood intensity – Baseline mood intensity), a MANCOVA controlling for gender and age indicated a marginal multivariate effect of Condition (*Pillai's Trace* = 0.91, *F*(20, 6) = 3.20, *p* = 0.077), suggesting potential divergence in emotional shifts. Follow-up univariate ANCOVAs were conducted to explore outcome-specific patterns across motivational, engagement-related, and affective mood dimensions relevant to collaborative learning. This revealed a pattern of greater increases in positive moods for the human teacher condition and greater increases in negative moods for the chatbot condition. Because the omnibus effect was marginal and the study was exploratory, these outcome-specific findings should be interpreted cautiously.

Follow-up regressions showed that effects were driven by greater increases in positive moods (Motivated, Inspired, Empowered, and Engaged) for participants in the human teacher group, with marginal gains in Excited and Connected. Conversely, the chatbot group showed significantly greater increases in negative moods – Stressed, Discouraged, Bored, and Distracted, with marginally greater Frustrated. Focused and Determined did not show significant condition effects in the regression models. Table 1 presents inferential statistics for mood change scores.

Perception of the brainstorming session

A MANCOVA was conducted to examine whether perceptions relating to the value and cognitive impact of the brainstorming session differed between the chatbot and human teacher conditions, while controlling for gender and age. The overall multivariate effect of Condition was statistically significant, *Pillai's Trace* = 0.82, *F*(15, 10) = 3.05, *p* = .040, indicating that participants' perceptions of the brainstorming session varied depending on the interaction partner. Follow-up ANCOVAs suggested that participants who brainstormed with a human teacher generally reported more positive perceptions of the session across several items. They were more likely to describe their brainstorming partner as knowledgeable and to feel more comfortable interacting. They were also more likely to indicate learning something new, and also find it easier to communicate ideas. Some additional differences, including enjoyment and perceived critical thinking, were of significance. Participants in the chatbot condition also reported marginally greater feelings of being judged and significantly greater perceptions of mental exhaustion during the brainstorming process. See Table 2 for descriptive and inferential statistics.

Despite these differences, both groups rated the session comparably in key outcome areas: they felt equally engaged, encouraged to consider different perspectives, and believed the session helped generate useful ideas and better prepared them for essay writing. Notably, both groups remained neutral on whether they believed a chatbot or a human would be more effective beforehand.

Physiological responses

Raw (unadjusted) summary measures (raw means and AUCs) for each physiological variable by condition and phase are reported in Supplementary Tables S3.2 and S3.3.

Baseline phase: Mean values and AUC

A MANCOVA on baseline mean values (controlling for age and gender) revealed a significant overall effect of Condition, *Pillai's Trace* = 0.347, *F*(3, 23) = 4.08, *p* = .02. Pulse was significantly higher in the chatbot than human condition, *F*(1, 25) = 11.00, *p* = .003, partial η^2 = .31, (*M* = 85.2, 95% *CI*[79.9, 90.5] vs. *M* = 73.8, 95% *CI*[68.3, 79.2]); EDA and Temperature did not differ between conditions (both *ps* > .19).

A MANCOVA on baseline AUCs also showed a significant effect of Condition, *Pillai's Trace* = 0.500, $F(3, 22) = 7.32$, $p = .001$, with higher pulse AUC in the chatbot condition, $F(1, 24) = 10.18$, $p = .004$, $M = 341$, 95% CI[318, 364] vs. $M = 295$, 95% *CI*[273, 318]), partial $\eta^2 = .30$, and marginally predicted Temperature ($F(1, 24) = 3.28$, $p = .08$), partial $\eta^2 = .12$, but not EDA ($p > .37$). Temperature AUC was marginally higher in the human condition (M =125, 95% *CI*[122, 127]) than the chatbot condition ($M = 122$, 95% *CI*[120, 124]).

Table 1. ANCOVA results for mood change scores by condition.

Mood	ANCOVA $F(1, 25)$, p	partial η^2	Condition β (SE)		Direction
Motivated Change	10.54, .003	0.3	0.84 (0.26)	**	Human > Chatbot
Inspired Change	8.09, .009	0.24	0.93 (0.33)	**	Human > Chatbot
Empowered Change	10.44, .003	0.29	0.86 (0.26)	**	Human > Chatbot
Engaged Change	11.36, .002	0.31	1.00 (0.30)	**	Human > Chatbot
Excited Change	3.53, .072	0.12	0.75 (0.49)	†	Human > Chatbot
Connected Change	3.53, .072	0.12	0.71 (0.38)	†	Human > Chatbot
Stressed Change	13.07, .001	0.34	-1.18 (0.33)	**	Human < Chatbot
Discouraged Change	11.65, .002	0.32	-1.00 (0.29)	**	Human < Chatbot
Bored Change	6.46, .018	0.21	-0.81 (0.32)	*	Human < Chatbot
Distracted Change	9.36, .005	0.27	-1.27 (0.41)	**	Human < Chatbot
Frustrated Change	3.64, .068	0.13	-0.64 (0.34)	†	Human < Chatbot
Determined Change	2.75, .110	0.1	0.47 (0.28)	-	-
Focused Change	2.89, .101	0.1	0.51 (0.30)	-	-

Note. *p values are two-tailed. * denotes p < .05, ** denotes p <.01, † denotes 05 ≤ p < .10. ANCOVAs controlled for gender and age. Partial η² values are reported for the Condition effect. β values represent adjusted Condition coefficients from the corresponding linear models, coded such that positive values indicate greater mood increases in the Human condition relative to the Chatbot condition*

Table 2. Descriptive and inferential statistics on participants' perceptions of the brainstorming session.

Item	*M* (SD) (Chatbot)	*M* (SD) (Human)	*F*(1, 25), *p*	partial η^2	β (SE)
1. The brainstorming session helped me generate useful ideas for my essay outline.	4.07 (0.80)	4.27 (0.88)	0.82, .375	0.03	0.27 (0.30)
2. I found the brainstorming partner to be knowledgeable.	3.20 (1.37)	4.53 (0.74)	11.93, .002 **	0.32	1.43 (0.42)
3. I feel better prepared to write my essay after the session.	3.87 (0.92)	4.20 (1.08)	0.75, .404	0.03	0.32 (0.38)
4. It was easy to communicate my ideas during the session.	3.40 (1.18)	4.20 (0.68)	4.92, .036 *	0.16	0.79 (0.36)
5. I felt judged during the brainstorming session.	2.27 (1.03)	1.60 (0.91)	3.10, .091	0.11	-0.57 (0.33)
6. I felt engaged throughout the brainstorming session.	3.80 (0.86)	4.27 (1.03)	1.65, .211	0.06	0.462 (0.36)
7. I enjoyed the brainstorming process.	3.60 (1.12)	4.27 (1.10)	4.23, .050	0.14	0.82 (.40)
8. The session maintained my interest in the topic.	3.64 (1.0)	4.53 (0.52)	8.56, .007**	0.26	0.92 (0.31)
9. I found the brainstorming process mentally exhausting.	2.53 (1.19)	1.53 (0.64)	6.93, .014 *	0.22	-0.93 (0.35)
10. The session challenged me to think critically about the topic.	3.27 (1.44)	4.07 (0.70)	3.66, .067	0.13	0.81 (0.42)
11. I was encouraged to explore different perspectives.	3.93 (1.16)	4.33 (0.82)	1.43, .243	0.05	0.45 (0.38)
12. I learned something new during the brainstorming session.	3.27 (1.39)	4.47 (0.52)	11.52, .002 **	0.32	1.27 (0.38)
13. I felt comfortable interacting with the brainstorming partner.	3.73 (1.22)	4.60 (0.83)	8.61, .007 **	0.26	1.03 (0.35)
14. I think brainstorming with a teacher/chatbot* would be more effective.	3.73 (1.03)	3.13 (1.41)	2.48, .128	0.09	-0.72 (0.45)
15. I communicate the same way when using an AI chatbot as when interacting with a human	2.20 (1.08)	1.80 (1.26)	2.60, .120	0.09	-0.60 (0.37)

Brainstorming phase: Mean values and AUC

A MANCOVA on mean physiological values during brainstorming (controlling for baseline pulse, EDA, temperature, gender, and age) yielded a significant multivariate effect of Condition, *Pillai's Trace* = 0.827, $F(3, 20) = 31.86$, $p < .001$. Follow-up covariate-adjusted ANCOVAs revealed no significant condition effect for pulse ($F(1, 22) = 0.57$, $p = .46$). However, condition was marginally associated with EDA ($F(1, 22) = 4.01$, $p = .058$, partial $\eta^2 = 0.15$) and significantly associated with temperature ($F(1, 22) = 6.73$, $p = .017$, partial $\eta^2 = 0.23$). Covariate-adjusted means for Pulse showed that heart rate was slightly higher in the chatbot condition ($M = 80.4$, 95% *CI* [78.1, 82.7]) than in the human condition ($M = 79.2$, 95% *CI* [76.9, 81.5]). EDA was lower in the chatbot condition ($M = 0.26$, 95% *CI* [-0.04, 0.56]) than in the human condition ($M = 0.68$, 95% *CI*[0.38, 0.99]). Adjusted temperature values were lower in the chatbot condition ($M = 31.3$, 95% *CI*[30.8, 31.9]) than in the human condition ($M = 32.3$, 95% *CI*[31.8, 32.8]) (Figure 2).

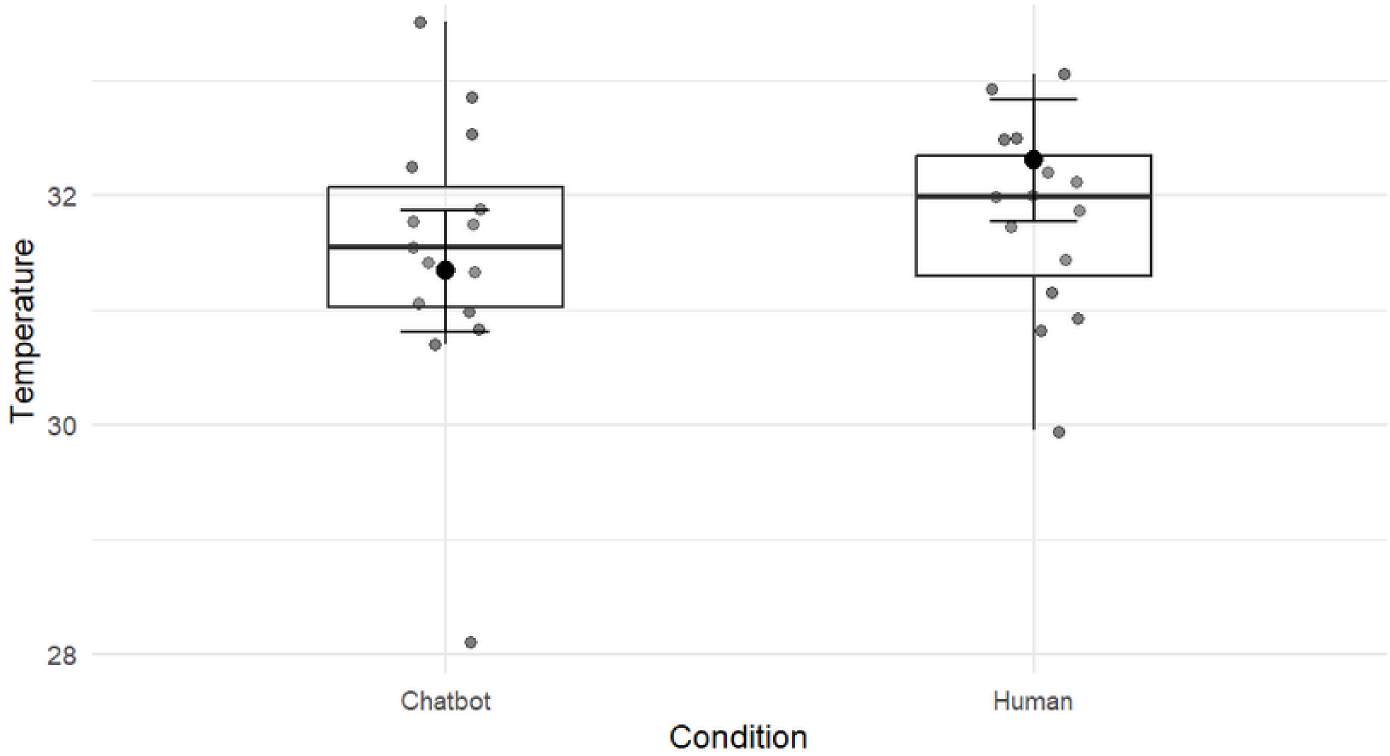

Figure 2. Temperature during brainstorming by condition.

Note. *Small jittered dots represent actual temperature values for each participant in each condition during brainstorming. Adjusted means from the regression model are the large black points with error bars, controlling for gender, age, baseline pulse, baseline EDA and baseline temperature.*

The corresponding AUC analysis showed a significant overall effect of Condition, *Pillai's Trace* = 0.864, $F(3, 19) = 40.36$, $p < .001$. Follow-up covariate-adjusted ANCOVAs, controlling for baseline physiological AUCs, gender, and age, revealed a significant condition effect for EDA AUC, $F(1, 21) = 5.23$, $p = .033$, partial $\eta^2 = 0.20$, but not for Pulse AUC, $F(1, 21) = 2.12$, $p = .160$, or Temperature AUC, $F(1, 21) = 0.76$, $p = .393$. Estimated marginal means indicated that cumulative EDA was higher in the human condition ($M = 18.7$, 95% *CI* [10.4, 27.0]) than in the chatbot condition ($M = 5.2$, 95% *CI* [-2.8, 13.2]) (Figure 3). In contrast, although Pulse AUC was descriptively higher in the chatbot condition ($M = 1917$, 95% *CI* [1871, 1964]) than in the human condition ($M = 1867$, 95% *CI* [1819, 1916]), and Temperature AUC was descriptively higher in the human condition ($M = 763$, 95% *CI* [754, 773]) than in the chatbot condition ($M = 757$, 95% *CI* [748, 767]), these differences were not statistically significant after adjustment for baseline physiology and demographic covariates. These findings suggest that the multivariate physiological differences observed between conditions were primarily reflected in cumulative electrodermal activity rather than sustained differences in pulse or temperature.

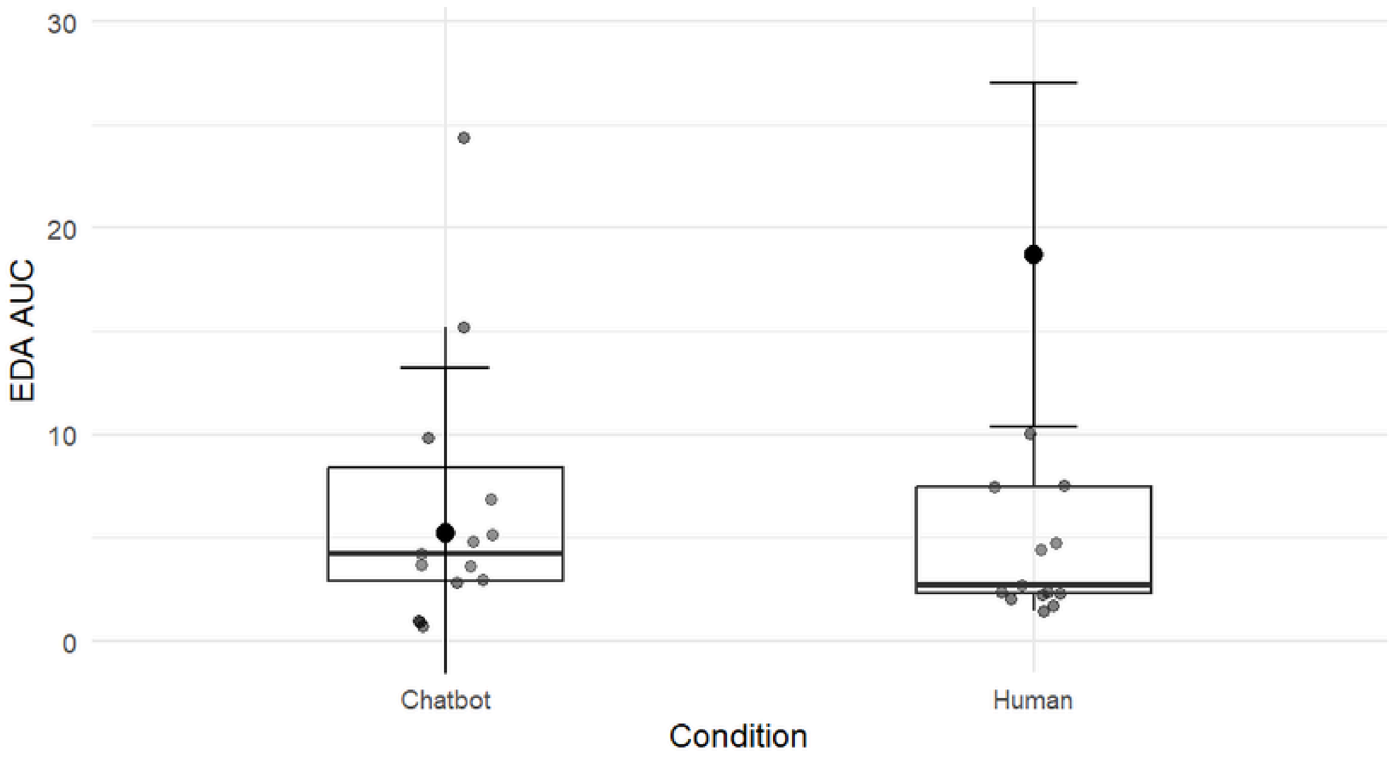

Figure 3. EDA AUC by Condition during Brainstorming (raw points and adjusted means). Three extreme EDA observations above 1.2 are not shown to improve visualisation; all observations were retained in statistical analyses.

Time series analysis

Linear mixed-effects models of minute-by-minute physiological data from the 25-minute brainstorming phase, with baseline values as covariates and random intercepts for participants, revealed no significant differences between the chatbot and human conditions in physiological change trajectories (all ps > .44). Full model outputs for each physiological measure are provided in Supplementary Material 4.

Predicting mood change through brainstorming from physiology (AUCs)

To investigate whether brainstorming mood could be explained by participants' physiological responses during the task, a series of regression models were fitted using AUC values (Pulse, Temperature, EDA) to predict mood change. Analyses were conducted at two levels: (1) aggregated positive/negative mood change scores, and (2) individual mood change outcomes.

Internal consistency of the positive and negative mood composites was assessed using Cronbach's alpha at baseline and post-brainstorming. The positive mood composite demonstrated excellent internal consistency at baseline (α = .90) and post-brainstorming (α = .88). The negative mood composite also demonstrated excellent internal consistency at baseline (α = .92) and post-brainstorming (α = .86).

Prior to regression analyses, assumptions were assessed through visual inspection of residual, Q-Q, scale-location, and leverage plots. Normality and homoscedasticity were further examined using Shapiro-Wilk and Breusch-Pagan tests, respectively. Diagnostic checks indicated no major violations of regression assumptions. Residuals were approximately normally distributed (Shapiro-Wilk p > .05), no evidence of heteroscedasticity was observed (Breusch-Pagan p > .05), and multicollinearity was low (all VIFs < 2).

For the composite negative mood change score, the regression showed that *Pulse AUC* positively predicted increased negative mood intensities (t(26) = 2.47, p = .02). Examining individual negative mood items, pulse AUC sig-

-nificantly predicted increased stress ($t(26) = 3.03$, $p = .006$), boredom ($t(26) = 2.25$, $p = .03$), and was marginally associated with discouragement ($t(26) = 1.96$, $p = .06$). Pulse AUC also showed a marginal negative association with positive moods ($t(26) = -1.98$, $p = 0.06$), with lower pulse AUC associated with feeling more empowered ($t(26) = -3.77$, $p < .001$), engaged ($t(26) = -3.18$, $p = .004$), connected ($t(26) = -3.12$, $p = .004$), and determined ($t(26) = -2.42$, $p = .02$).

Temperature AUC emerged as a predictor of mood outcomes, showing a marginally positive relationship with composite positive mood change ($t(26) = 2.02$, $p = .05$). Specifically, higher temperature AUC significantly predicted increases in positive moods such as empowered ($t(26) = 3.54$, $p = .002$), connected ($t(26) = 2.93$, $p = .007$), and inspired ($t(26) = 2.13$, $p = .04$). Additionally, excitement was also marginally predicted by Temperature AUC ($t(26) = 1.80$, $p = .08$). Conversely, lower temperature AUC was associated with stronger negative emotional responses, including feeling more frustrated ($t(26) = -2.20$, $p = .04$), and marginally more stressed ($t(26) = -1.78$, $p = .087$).

For the composite positive and negative mood change scores, EDA AUC was not a significant predictor. However, at the individual level, it was positively associated with increased stress ($t(26) = 2.48$, $p = .02$), and was marginally associated with feeling less connected ($t(26) = -1.81$, $p = .08$), less confused ($t(26) = -2.02$, $p = .05$), and feeling less challenged ($t(26) = -1.72$, $p = .098$).

Discussion

Mood

At baseline, the mood ratings between the two conditions (Chatbot vs. Human) were not significantly different. Descriptively, participants in both conditions reported higher positive mood intensities following the brainstorming session, suggesting that brainstorming itself was associated with a generally positive emotional experience. Although the overall multivariate mood effect was marginal and the study was exploratory, the outcome-specific analyses suggested that participants in the human teacher condition experienced greater increases in several positive moods and greater reductions in several negative moods than those in the chatbot condition. In particular, participants in the human teacher condition showed a greater increase in positive feelings, such as “Motivated”, “Inspired”, “Empowered”, and “Engaged”, than those who interacted with the chatbot. Conversely, those in the chatbot condition experienced increased intensities in several negative moods, while those in the human condition experienced a decrease. These findings suggest that although both interaction types were associated with positive emotional gains, the emotional experiences associated with brainstorming differed between the chatbot and human-facilitated conditions.

Although the human-led condition elicited greater emotional improvements overall, the intensity change for many mood states – both positive and negative, such as “Focused”, “Curious”, “Confident”, “Determined”, “Confused”, “Challenged”, “Overwhelmed”, “Anxious”, and “Annoyed” – did not differ significantly between groups. This highlights that the chatbot’s ability to support a wide range of engagement-related emotional states should not be discounted. Moreover, not all negative emotions are detrimental; moods like frustration or feeling challenged can be facilitative of learning, reflecting productive cognitive effort. This experience, also known as cognitive disequilibrium, arises when individuals engage with unfamiliar material that signals knowledge gaps or conflicts with their existing knowledge (Piaget, 2005/1950). To resolve this tension and move forward, individuals are driven to assimilate new information into existing schemas or accommodate by adjusting their schemas. Thus, certain “negative” emotions may indicate meaningful cognitive engagement and can even be beneficial for deeper learning.

Perceptions of the brainstorming session

Participants’ perceptions of the brainstorming session were generally positive, ranging from 3.20 to 4.60, with those who interacted with the human teacher rating their experience more positively. For several aspects, these group differences were significant. This included finding the human teacher more knowledgeable, feeling more comfortable interacting with the human teacher, being more likely to indicate having learnt something new, and also finding it easier to communicate ideas. Conversely, those in the chatbot condition found the experience more mentally taxing and were marginally more likely to feel judged. One possible explanation is the way the chatbot was designed to intentionally avoid providing direct answers. Instead, it was designed to use a Socratic approach and engage participants with a series of question prompts aimed at helping them to think critically and consider different perspectives to ultimately come up with original ideas. While this approach aligns with educational goals of fostering deeper thinking, it may have deviated from participants' usual experience with GenAI tools such as ChatGPT, tools that often provide more immediate and "fuller answers". As a result, participants may have perceived the chatbot interaction as more cognitively demanding, leading to greater fatigue or frustration.

Despite the differences noted between conditions, both groups rated the brainstorming session comparably on key outcome areas. Participants across both conditions felt engaged throughout, challenged to think critically, encouraged to consider different perspectives, and believed the session helped them to generate useful ideas and better prepared them for essay writing. These findings highlight the value of human interaction in fostering a sense of comfort, perceived expertise, and cognitive ease, while also suggesting that GenAI chatbots – despite limitations in emotional nuance – can still support core learning aspects like engagement, intellectual stimulation and critical thinking. Notably, both groups remained neutral when asked, after the brainstorming session, whether they believed a chatbot or a human would be more effective. This suggests that despite differences in user experience, both interaction types were perceived as similarly effective in achieving the goal of the task – generating ideas for an essay outline.

Physiological responses

The adjusted physiological analyses suggested condition differences in peripheral temperature and cumulative electrodermal activity, whereas pulse-related differences were largely explained by baseline physiological variation. Human-facilitated brainstorming was associated with higher peripheral temperature and greater cumulative electrodermal activity than chatbot-facilitated brainstorming. These findings present a more multifaceted picture than the self-report measures alone. Consistent with embodied and interoceptive perspectives of emotion (Barrett & Simmons, 2015), subjective evaluations and physiological responses may capture different dimensions of learner experience. While participants in the human condition reported more positive emotional experiences and perceptions of the brainstorming session, the physiological data did not indicate a simple pattern of greater or lesser engagement across conditions.

One possible interpretation is that the higher temperature and cumulative EDA observed in the human condition reflect greater interpersonal engagement, social responsiveness, or affective involvement during human-facilitated brainstorming. At the same time, the mood findings suggest that participants in the chatbot condition experienced greater increases in several negative emotions. This pattern may indicate that the chatbot interaction was experienced as more effortful or cognitively demanding, potentially due to its Socratic questioning approach, which encouraged participants to generate and refine their own ideas rather than receive direct answers. Importantly, such experiences are not necessarily detrimental and may reflect productive cognitive effort associated with deeper reflection and idea generation.

However, the time series analysis using mixed-effects modelling revealed no significant differences between conditions in physiological change trajectories over the 25-minute brainstorming session, once baseline AUC, gender and age were controlled. Despite differences in mood and perceived cognitive impact, both interaction types elicited similar patterns of physiological change across time. These findings suggest that human and GenAI chatbot-facilitated brainstorming may foster physiological engagement through different pathways: human facilitation may provide greater social and emotional support, whereas chatbot facilitation may encourage more effortful forms of cognitive engagement. The absence of systematic physiological trajectory differences further suggests that chatbot-supported brainstorming can sustain meaningful learner engagement and may serve as helpful pedagogical aids for the teacher.

Prediction of mood from physiology

Pulse AUC was positively associated with increased negative moods (stress, discouragement, boredom), and negatively with positive moods (empowerment, engagement, connection, determination). This pattern is consistent with research linking heart rate to emotional valence and cognitive effort (e.g., Darnell & Kreig, 2019). It is also consistent with the biopsychosocial model of challenge and threat (Seery, 2011), which proposes that individuals' appraisals of demanding situations are accompanied by differing physiological responses. Although the present study cannot determine the precise mechanisms underlying these associations, the findings suggest that sustained cardiovascular activation during brainstorming may be related to less favourable emotional experiences.

Temperature AUC was marginally associated with increases in positive mood intensity (empowered, connected, inspired, and excitement), and negatively associated with negative mood change, including frustration and marginally increased stress. This pattern is aligned with research linking positive emotional engagement with higher skin temperature and autonomic processes (Hayashi et al., 2006; Stefano et al., 2008). Participants reporting more positive emotional experiences generally exhibited higher temperature AUC values, whereas those reporting greater frustration and stress tended to show lower temperature AUC values. Taken together with the Pulse AUC findings, the findings suggest that positive and negative emotional experiences during brainstorming were associated with distinct physiological profiles. However, the mechanisms underlying these associations cannot be determined from the present data and require further investigation.

EDA AUC was positively related to increased stress, consistent with its role as an indicator of sympathetic nervous system activation (Akbulut, 2022). Associations with other mood outcomes were less consistent and should be interpreted cautiously, suggesting that the relationship between electrodermal activity and emotional experience during brainstorming may be more complex and warrants further investigation.

Regardless of condition, pulse and temperature AUCs were also systematically linked to mood variation across participants, independent of facilitator type. Although causality cannot be inferred, this convergence suggests that these physiological indicators were associated with emotional variation across participants and reflect core bodily processes underpinning participants' emotional experiences during the task, whether interacting with a human or a chatbot. This convergence between mood reports and physiological activity suggests that subjective emotional experiences were accompanied by measurable real-time bodily experiences, supporting the view that emotional engagement during collaborative learning is both subjectively experienced and physiologically embodied.

Importantly, the associative patterns of physiological markers, particularly Pulse and Temperature AUC, suggest that beyond group-level differences, the pattern and emotional meaning of physiological activation differ across individuals. Higher pulse AUC was associated with more negative mood states, while higher temperature AUC was associated with increases in positive emotions. These results indicate that participants' emotional experiences during the session were not fully reflected by group averages alone, but also by how their bodies responded within each condition. Although these associations should be interpreted cautiously given the exploratory nature of the study, they highlight the potential value of looking beyond group-level comparisons to examine within-individual variation. Future research employing multimodal approaches that integrate self-report, behavioural, and physiological measures may help identify how different forms of AI-supported interaction are experienced by learners and which interaction characteristics are associated with more positive emotional experiences. Such work could contribute to the development of more emotionally responsive and pedagogically effective GenAI-supported learning environments.

While physiological data provided insights into participants' emotional and cognitive states, it is important to note that in future studies of this nature, physiological responses alone are unlikely to reliably distinguish between the chatbot and human conditions. Physiological metrics, though valuable, should be interpreted alongside subjective and behavioural measures to gain a more holistic understanding of user experiences. Relying solely on physiological data may obscure subtle differences that may only emerge through self-report or qualitative data, while relying solely on subjective data may overlook meaningful physiological patterns. Because these analyses involved multiple exploratory regression models, the observed associations should be regarded as preliminary and require replication in larger samples.

Notwithstanding, our findings have partially supported the first hypothesis that learners who engage in brainstorm-

-ing with a human teacher. On the one hand, participants in both conditions reported positive emotional gains following the brainstorming session, and many positive mood states, including feeling focused, curious, confident, and determined, did not differ significantly between conditions. Both groups also reported comparable levels of engagement, critical thinking, perspective-taking, and perceived usefulness of the brainstorming session. These findings suggest that GenAI chatbots can foster many of the positive emotional and engagement-related experiences traditionally associated with human-facilitated brainstorming. On the other hand, participants in the human teacher condition reported significantly greater increases in several positive emotions, including feeling motivated, inspired, empowered, and engaged. They also perceived the facilitator as more knowledgeable, felt more comfortable during the interaction, and were more likely to report learning something new. These findings indicate that while chatbot-facilitated brainstorming can support positive emotional experiences, it did not fully replicate the emotional benefits associated with human facilitation.

The second hypothesis that learners who engage in brainstorming with a GenAI chatbot will report lower levels of negative emotional states than learners who engage in brainstorming with a human teacher is not supported. Rather than reporting lower levels of negative emotion, participants in the chatbot condition experienced increases in several negative mood states, whereas participants in the human teacher condition generally showed reductions in these emotions. Participants who interacted with the chatbot also perceived the brainstorming session as more mentally taxing. As mentioned earlier, one plausible explanation is the chatbot's Socratic questioning strategy, which intentionally encouraged participants to generate and refine their own ideas rather than receive direct answers. While this approach may have promoted deeper thinking, it may also have increased cognitive effort and emotional strain. Importantly, these negative emotional experiences should not necessarily be interpreted as undesirable. Emotions such as confusion, challenge, and frustration may reflect productive cognitive disequilibrium and deeper engagement with the learning task.

Our findings also have mixed evidence for the final hypothesis that learners who engage in brainstorming with a GenAI chatbot will exhibit physiological patterns indicative of similar emotional regulation and lower stress compared with learners who engage in brainstorming with a human teacher. The prediction that chatbot-facilitated brainstorming would produce lower stress responses than human facilitation was not clearly supported. Participants in the human teacher condition exhibited higher peripheral temperature and greater cumulative electrodermal activity than those in the chatbot condition, suggesting that human-facilitated brainstorming elicited stronger physiological activation. However, the interpretation of these differences is not straightforward. Higher temperature was associated with more positive emotional experiences, whereas greater electrodermal activity may reflect heightened engagement, social responsiveness, or emotional involvement rather than stress alone. More importantly, mixed-effects modelling revealed no significant differences between conditions in physiological change trajectories across the 25-minute brainstorming session after controlling for baseline physiological variation. This finding suggests that, despite differences in subjective emotional experiences, both human- and chatbot-facilitated brainstorming elicited broadly similar patterns of physiological engagement over time. Rather than demonstrating reduced physiological activation, chatbot-facilitated brainstorming appeared to sustain levels of physiological engagement comparable to those observed during human-facilitated brainstorming. Human facilitation may have promoted greater social and emotional involvement, whereas chatbot facilitation may have encouraged more effortful cognitive engagement.

Limitations

Several limitations should be considered when interpreting the findings. First, the study involved a relatively small sample (N = 30), which limits statistical power and the stability of parameter estimates, particularly given the multivariate and exploratory analyses conducted. In addition, the large number of outcome-specific analyses increases the possibility of inflated Type I error. Although effect sizes were reported alongside significance tests, the findings should be regarded as preliminary and interpreted with appropriate caution. Furthermore, the modest sample size relative to the number of predictors included in some models raises the possibility of model instability and overfitting. Replication with larger and more diverse samples is therefore needed to establish the robustness and generalisability of the observed patterns.

Second, the study examined a single collaborative brainstorming task within a higher education context. Participan-

-ts engaged in brainstorming ideas for an essay on Singlish, and emotional and physiological responses may differ across other learning activities, disciplinary domains, educational levels, and cultural contexts. Future research should investigate whether similar patterns emerge across a broader range of writing, learning, and problem-solving tasks.

Third, the human facilitation condition involved a single instructor. Although this approach ensured consistency across participants, it is possible that some findings reflect characteristics of the individual facilitator rather than human facilitation more generally. Future studies could incorporate multiple instructors and examine instructor-related variability to strengthen the external validity of comparisons between human and AI-supported learning interactions.

Fourth, significant baseline differences were observed for pulse-related measures between conditions. Although baseline physiology was statistically controlled in subsequent analyses, these initial differences complicate interpretation of condition effects and may have influenced the stability of the physiological findings. Future work with larger samples and enhanced baseline standardisation procedures would help establish the stability of these effects.

Finally, the chatbot used in this study was a purpose-built system designed to support essay planning and brainstorming. The findings should therefore not be assumed to generalise to other generative AI systems, interfaces, prompting approaches, educational activities, learner populations, or disciplinary domains. As conversational AI technologies continue to evolve rapidly, future research should compare different chatbot designs and levels of pedagogical scaffolding to determine which features most effectively support positive emotional experiences and sustained learner engagement. Replication studies should also be considered across larger and more diverse samples, learning contexts, and instructional designs.

Conclusion

While chatbots are not necessarily superior to human teachers, they are also not demonstrably worse in many respects. Both groups in our study experienced emotional gains, reflected in improved mood. Perceived effectiveness, as expressed through their questionnaire responses, was also high across both conditions. Importantly, the chatbot environment still supported key aspects of cognitive and motivational engagement.

Pedagogically, the findings reaffirm the enduring value of the human teacher in engaging and motivating the students. Participants consistently rated the human teacher more favourably across multiple dimensions – comfort, enjoyment, learning gains, and ease of communication – emphasising the irreplaceable role of human empathy, adaptability, and non-verbal reassurance in teaching. Notwithstanding, the study also makes a strong case for the educational viability of GenAI chatbots, particularly as cognitive partners that can stimulate reflection and critical thinking. Despite limitations in emotional warmth, the chatbot condition still supported high levels of engagement and intellectual challenge, as evidenced by both self-reports and physiological data. These findings provide preliminary evidence that, when designed thoughtfully, chatbots can serve as scalable pedagogical aides that can support the teacher's design of the learning experience. Its value is especially apparent under circumstances where it is advantageous to have round-the-clock availability, personalised and objective tutoring. They can help mitigate the practical and time constraints that often limit human teaching capacity, despite being unable to fully replicate the nuances of ideal human interaction.

Our study contributes to the understanding of the relationship between learning and emotion in the use of GenAI for education. Our study is premised on the recognition that learning is not only a cognitive activity but also a deeply emotional and physiological experience. The observed mood shifts, particularly the greater positive emotional gains in the human teacher condition, highlight the importance of relational dynamics and perceived emotional presence in shaping students' receptivity and engagement.

Our study employs a multimodal, mixed-methods approach that integrates self-reported mood and continuous physiological tracking. This design enhances the reliability of emotional data by triangulating subjective experiences with physiological indicators such as electrodermal activity (EDA), pulse, and skin temperature. In doing so, it mitigates common limitations of self-report measures – such as social desirability bias and retrospective inaccuracies. The integration of physiological data also offers empirical evidence that emotional states are not only subjectively experienced but physiologically embodied. The observed associations between physiological markers – particularly skin temperature and heart rate – and learners' emotional experiences are consistent with multimodal perspectives on embodied teaching (Lim, 2020) and learning (Barsalou, 2008), which emphasise the integration of affective, cognitive, and bodily processes during learning activity.

The use of AUC and growth curve modelling of physiological data offers methodological contribution in capturing sustained emotional and cognitive engagement over time, rather than relying on static point measurements. These techniques illuminate not just whether physiological differences exist, but how they unfold across learning episodes. The analyses were intended to strengthen interpretation by accounting for baseline individual variability and contextual factors such as age and gender. Our study also contributes towards a replicable methodological template for future studies aiming to assess affective receptivity and engagement in human–AI interaction, particularly in educational contexts where physiological data can complement more traditional outcome measures.

While the study has found that the GenAI chatbot was able to increase students' positive moods, thereby motivating them in their learning, a limitation in this study relates to the design of the chatbot we used. Our chatbot was programmed to use a Socratic questioning approach to promote critical thinking; however, some participants reported feeling mentally exhausted or frustrated as it was atypical of the usual chatbots they had used, which would offer them answers directly. Future iterations of the chatbot could incorporate adaptive mechanisms to detect circular or stalled conversations and provide more direct information or examples when necessary, which may help reduce students' feelings of frustration. Feedback from the participants also suggests that the chatbot would benefit from emotional augmentation features, such as detecting and responding to signs of user frustration in real time (Arguel et al., 2019), adjusting its tone to match that of participants, and explicitly acknowledging their effort or confusion, in order to generate greater perceived feelings of empathy and support.

Ultimately, it is essential to recognise that AI chatbots and human teachers are fundamentally different (e.g., communication styles, adaptability, sensitivity to nuance). Finding the right fit between learner needs and the type of facilitator will likely be complex, and there is unlikely to be a single, universal solution. An important value that GenAI affords is the myriad ways that the chatbots can be designed for different educational purposes and audiences. For example, some contexts may benefit from highly structured, informative chatbots, while others might require more conversational agents that are capable of providing emotional support and nuanced dialogue. Future work could explore how different learners respond to varying levels of cognitive and emotional support from GenAI chatbots to inform the development of personalised chatbot designs that can effectively support a variety of pedagogical innovations.

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Supplementary material

Supplementary material for this article (including chatbot prompts, mood questionnaire, and descriptive statistics for mood and physiological data) is provided in a single accompanying file. Access it here: https://jalt.open-publishing.org/index.php/jalt/libraryFiles/downloadPublic/95

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