EduEmotion: An EEG Dataset of Emotional Responses in Simulated Learning Tasks

M. Luiza R. Menezes, Rosa Maria Vicari

Programa de Pós Graduação em Informática na Educação
Universidade Federal do Rio Grande do Sul (UFRGS)
Porto Alegre – RS – Brazil

luiza.menezes@ufrgs.br, rosa@inf.ufrgs.br

Abstract. *This paper presents EduEmotion, an EEG-based dataset designed to support emotion recognition in distance education. It captures affective dynamics during self-guided, domain-neutral digital interactions that reflect common online learning experiences. Data from 22 participants contain EEG signals and self-reported emotions. The study emphasizes the representativeness of emotional responses in authentic educational scenarios and the elimination of disciplinary bias. Results show consistent patterns of engagement and mild frustration—emotional states common in remote learning—providing a realistic foundation for adaptive educational technologies.*

Resumo. *Este artigo apresenta o EduEmotion, um conjunto de dados baseado em EEG voltado ao reconhecimento de emoções na educação a distância. A base registra dinâmicas afetivas durante interações digitais neutras e autoguiadas, representativas de experiências comuns de aprendizagem online. Reúne sinais de EEG e autorrelatos emocionais de 22 participantes. O estudo valoriza a representatividade das respostas emocionais em cenários educacionais autênticos e a eliminação de viés disciplinar. Os resultados indicam padrões consistentes de engajamento e frustração leve — estados típicos da aprendizagem remota — fornecendo uma base realista para o desenvolvimento de tecnologias educacionais adaptativas.*

1. Introduction

In learning sciences, emotions are widely acknowledged as powerful mediators of engagement, motivation, and knowledge retention (D'Mello and Graesser 2021; Holmes and Bialik 2022; Picard 1997). Rather than treating affective states as peripheral, educational research increasingly frames them as key components in adaptive and personalized systems. By detecting emotional shifts in real time, technology-enhanced learning platforms can tailor content difficulty, pacing, or learning pathways to each student's evolving needs (Woolf and Burleson 2019; Rodríguez et al. 2020).

A promising but still emerging methodology for capturing such moment-to-moment affect is electroencephalography (EEG) (Lin et al. 2019a; Coan and Allen 2004). Beyond observing external signals like facial expressions or body posture, EEG measures subtle neural dynamics that can precede overt indicators of stress, engagement, or confusion. Recent advances in portable EEG headsets have pushed this approach closer to

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real-world educational and distance learning contexts, albeit with open questions around wearability and signal robustness.

This work aims to bridge lab-based EEG findings and day-to-day classroom practices by presenting a dataset tailored to educational scenarios. While most EEG emotion datasets are built around passive entertainment stimuli, our study focuses on cognitively meaningful, domain-neutral tasks that resemble distance learning routines.

Specifically, we pursue four key objectives:

- To create an EEG dataset directly applicable to educational contexts, rather than entertainment or media consumption.
- To capture realistic emotional responses during neutral digital tasks that simulate the dynamics of distance and self-guided learning.
- To support the research community in developing emotion-aware educational technologies, especially in adaptive and affect-sensitive systems.
- To ensure ethical and inclusive design, with tasks free of disciplinary bias, anonymized data handling, and considerations for device usability.

By situating EEG-based affect detection in the broader literature on educational technology and affective computing, we highlight both the promise and the complexities of implementing such systems at scale. From the possibility of detecting early frustration in remote online learning courses or self-paced modules, to the development of reproducible datasets that support benchmarking and cross-study comparisons, our investigation underscores a need for interdisciplinary collaboration. Researchers, educators, and developers can benefit from new, task-grounded datasets that combine signal quality with ecological validity.

We propose this dataset as a foundational step toward improved modeling, evaluation, and application of affective computing in educational contexts. We aim to contribute a resource that informs future work on adaptive systems and supports the design of emotion-recognition algorithms grounded in real learning scenarios.

2. Related Work

Affective computing in education has gained traction over the last decade as researchers recognize the profound influence of emotional states on learning outcomes. Theories of emotionally adaptive learning suggest that early detection of frustration, disengagement, or confusion can help optimize instructional design and support (D'Mello and Graesser 2021; Woolf and Burleson 2019; Holmes and Bialik 2022). While early approaches focused on external signals such as facial expressions (McDaniel et al. 2018), body posture (Sun and Li 2022), or chat sentiment, these cues are often unreliable across individuals and cultural contexts.

Electroencephalography (EEG) has emerged as a complementary method to assess internal emotional states, offering the possibility to detect affective and cognitive responses even before they manifest behaviorally (Lin et al. 2019a; Coan and Allen 2004). Landmark datasets such as DEAP (Koelstra et al. 2012) and AMIGOS (Miranda-Correa et al. 2021) have enabled progress in EEG-based emotion recognition by providing standardized recordings in entertainment or social settings. However, these datasets typically rely on passive media consumption (e.g., watching music videos or short films), limiting their applicability to cognitively demanding educational environments.

Only a few datasets have attempted to capture emotions in learning scenarios. The DAiSEE dataset (Gupta et al. 2016) includes webcam recordings labeled for engagement, boredom, and frustration during MOOC-style video watching, but it does not use EEG. The CASE dataset (Ashwin et al. 2021) combines EEG with eye tracking during multiple-choice assessments, but its scope is limited to test-like settings rather than diverse learning activities. The SEED dataset (Zheng et al. 2015) incorporates emotion induction via film clips with EEG signals, but without educational tasks or real-time reporting.

In contrast, the EduEmotion dataset is designed around cognitively grounded, task-based interactions that reflect real distance learning or classroom activities, such as file navigation, spreadsheet manipulation, and timed quizzes. Each session collects EEG signals and self-reported affective ratings using the Self-Assessment Manikin (SAM) after each task, allowing emotional state mapping in realistic instructional contexts. This approach fills a gap in the literature by prioritizing emotion elicitation through goal-oriented tasks rather than passive stimuli.

Thus, EduEmotion contributes a novel, ethically conscious dataset that bridges affective computing and real-world educational practice. Its methodological choices reflect both practical concerns (e.g., wearability, task realism) and broader theoretical ambitions: to model affect not as a static label but as an evolving, context-sensitive process embedded in learning activities.

3. Methodology: Dataset Design and Collection

This section outlines the procedures used to design, implement, and document the EduEmotion dataset. Our methodology includes participant recruitment, task design, EEG signal acquisition, and emotion labeling. By combining behavioral and physiological data in domain-neutral tasks, we aim to support reproducible research in affective computing for education while ensuring ethical data handling and usability.

This is an applied experimental study conducted at Ulster University, Belfast, Northern Ireland. Participants were 22 staff and students with similar levels of computer experience. Data collection took place between June and July 2016 at the Artificial Intelligence Application Research Group (AIARG) laboratory. All participants provided informed consent, and the study was approved by the Ulster University Ethics Filter Committee (ref. FCE 20160419 16.24).

3.1. Participants and Ethics

A total of 22 adult volunteers participated in the study, including undergraduate and graduate students as well as university staff from a range of disciplines. Participants ranged in age from 19 to 48 years (mean = 27.3, SD = 6.9), with 13 identifying as female and 9 as male. Academic backgrounds included the humanities, natural sciences, and applied fields such as engineering and biology, which introduced variability in prior experience with technical or analytic digital tasks.

To avoid biasing emotional responses based on subject familiarity, we intentionally avoided tasks drawn from traditional educational content (e.g., course modules, lectures, or subject-specific assessments). Instead, we curated a set of domain-neutral digital tasks—file navigation, online item search, spreadsheet manipulation, and simple gameplay—that were cognitively engaging but did not rely on prior knowledge from any particular field. This allowed us to induce comparable levels of effort, confusion, or focus across participants, without favoring participants from any specific area of academic expertise.

Because participants differed in prior knowledge, technical skills, and familiarity with the types of tasks involved, we designed the session to minimize bias related to domain expertise. Instructions were standardized, and all tasks were chosen or adapted to offer a consistent level of challenge across users. For example, spreadsheet tasks involved simple formula edits and sorting operations, while online navigation activities were conducted in controlled interfaces with uniform language and structure. This strategy allowed us to induce mild but comparable emotional responses across participants without relying on prior exposure to specific content areas.

All participants provided informed consent prior to the session. The study was conducted in accordance with Ulster University's ethical guidelines and approved by the university's Research Ethics Committee. The study was approved by the Ulster University Ethics Filter Committee (ref. FCE 20160419 16.24) and the dataset is restricted under UK GDPR provisions governing special category biometric data. No personally identifying information was stored in the final dataset, and participants were informed that their data would be anonymized and used solely for research purposes.

3.2. Task Design and Protocol

To simulate affective dynamics commonly observed in remote learning contexts, we structured four digital tasks that elicited mild cognitive load and emotional variation without relying on prior subject-matter expertise. These activities—file navigation, online search, spreadsheet editing, and a simple arcade-style game—were chosen to reflect goal-oriented interactions found in online learning environments, such as organizing course materials, solving practical problems, or navigating timed assessments.

Each task was designed to maintain a balance between challenge and accessibility. File navigation required participants to locate, rename, and sort documents under mild pressure; online search involved identifying specific items within a constrained interface; spreadsheet tasks focused on basic operations like summing and sorting; and the arcade game introduced time pressure and escalating difficulty to evoke arousal.

Importantly, user interface elements were standardized across tasks to reduce unintended variability, and instructions were crafted to ensure uniform comprehension regardless of participants' digital backgrounds. This design emphasized emotional fluctuation arising from interaction itself—rather than content familiarity—allowing the protocol to surface patterns of focus, confusion, or engagement applicable to diverse educational scenarios.

Task List and Rationale. Four distinct tasks were selected to approximate everyday interactions that learners might encounter in online or blended courses, resource-room support, or self-guided tutorials:

1. *File Navigation*: Locating, sorting, and renaming files in a simulated folder hi-

erarchy. This activity was intended to induce mild organizational challenge and occasional frustration, comparable to managing digital course materials or retrieving class documents in a learning management system.

2. *Online Shopping Simulation*: Browsing a simplified e-commerce platform within a set time limit to locate specified items. Although not strictly academic, the procedure represents generic web-based interactions (such as searching for references, online quizzes, or library databases) that require focused attention. We also adjusted the language settings to be uniform and slightly less familiar to some participants, ensuring that the difficulty level remained consistent across different backgrounds.
3. *Spreadsheet Manipulation*: Completing basic data entry or formula editing in a spreadsheet. This aligns with the kind of numeric or tabular work students might face in STEM assignments, lab reports, or collaborative resource-room tasks. Because participants possessed varying math and software skills, we crafted the spreadsheet prompts to be relatively universal (e.g., summing columns, sorting data) rather than advanced concepts where prior expertise would skew results.
4. *Gameplay at Varying Difficulty*: A simple "arcade" game reminiscent of *Pac-Man*, presented in both easy and challenging modes. We included this ludic element to induce transient stress or surprise, paralleling the emotional swings learners can experience when tackling progressively difficult e-learning modules or timed quizzes.

To ensure that all participants confronted similar levels of novelty and potential frustration, we standardized user-interface settings (e.g., language, layout, and fonts) so that no one had an excessive advantage or familiarity with the platform. Further, we avoided domain-specific instruction (e.g., advanced programming tasks) that might unfairly benefit participants with specialized expertise.

Link to Online Learning and Real-Class Settings. Although administered in a controlled lab, these tasks reflect key aspects of distance-education scenarios. File navigation and spreadsheet manipulation evoke the routine workload of students uploading homework or organizing digital research materials, while web browsing under time constraints mimics the stress of searching for credible sources or exam details in online platforms (Bai and Liu 2024; Zhou and Kim 2023). The brief arcade game addresses the notion that many e-learning resources now incorporate gamified components, fostering rapid emotional fluctuations akin to high-pressure quizzes or adaptive question banks. Because participants varied widely in their familiarity with these activities, the tasks served to replicate the uneven skill distribution found in typical online learning scenarios.

EEG Device Setup and Sampling. All neural signals were recorded using a 14-channel Emotiv EPOC headset. Each channel is positioned over key frontal, temporal, and parietal sites, capturing the frequency ranges most relevant for measuring affective states (Lin et al. 2010; Jenke et al. 2014; Mendoza et al. 2019; Menezes et al. 2017). Sampling was set at 128 Hz, ensuring a balance between comfort (through fewer electrodes) and resolution sufficient for feature extraction. Prior to each recording, electrode contact was verified, and participants were instructed on how to minimize extreme head movements.

Implementation Details. The tasks followed a fixed sequence for consistency, with short breaks (2–3 minutes) between them to reset any lingering emotional or cognitive states.Because participants had no homogenous background, we also replaced domain-specific text with standardized instructions to create uniform levels of potential boredom, confusion, or mild stress. In so doing, the setup aimed to produce a broader sampling of engagement/disengagement patterns without depending on prior content knowledge.

By unifying these four tasks within a single session and tailoring language or prompts to ensure consistent challenge levels, we sought to generate EEG data that captured genuine fluctuations in emotional and cognitive states. This design thus offers an initial demonstration of how EEG monitoring might integrate into daily study routines in e-learning or resource-room settings where learners have distinct aptitudes and may not outwardly signal frustration until it significantly impedes their progress.

3.3. EEG Setup and Signal Acquisition

EEG signals were acquired using a portable Emotiv EPOC headset (Inc. 2013; Mendoza et al. 2019), consisting of 14 saline-based sensors positioned in accordance with the international 10–20 system over frontal, temporal, parietal, and occipital regions. Sampling was set to 128 Hz, a rate deemed sufficient for capturing frequency bands associated with arousal and attentional states without overly complicating real-time processing (Lin et al. 2010; Jenke et al. 2014). Prior to each recording, electrode contact quality was checked, and participants were asked to limit head or jaw movements to minimize motion artifacts.

Raw EEG data were stored locally during each task and processed to remove ocular and muscle artifacts via a standard bandpass filter (1–50 Hz). Additionally, an automated artifact-removal step was applied to detect and correct high-amplitude transients such as blinks or sudden head shifts (Murugappan et al. 2010; Lin et al. 2019b). To mitigate potential drift over longer tasks, each participant's baseline was re-evaluated at the beginning of the session, ensuring that abrupt changes in signal amplitude could be attributed more reliably to emotional or cognitive shifts.

3.4. Emotion Labeling and Self-Reports

Following each activity (file navigation, online shopping, spreadsheet manipulation, or game), participants were instructed to self-report their affective experience using the Self-Assessment Manikin (SAM), a pictorial rating scale for *valence* (pleasant–unpleasant) and *arousal* (calm–excited) (Bradley and Lang 1994). As shown in Figure 1, the top row depicts the valence dimension, ranging from a frowning, unhappy figure (low valence) to a smiling, happy figure (high valence). The bottom row represents arousal, ranging from a relaxed, low-energy figure (low arousal) to an excited, high-energy figure (high arousal). Participants indicated their subjective state on a 1–9 scale for each dimension.

These two dimensions align with Russell's circumplex model, wherein emotional states can be mapped onto a coordinate plane of valence and arousal (Russell 1980). By aggregating the numeric scores into thresholds, we balanced resolution with the practicality of training separate classifiers for distinct emotional states.

3.5. Dataset Structure

To provide an integrated overview, Table 1 summarizes the main elements of the Edu-Emotion dataset, including participants, task design, EEG acquisition parameters, and

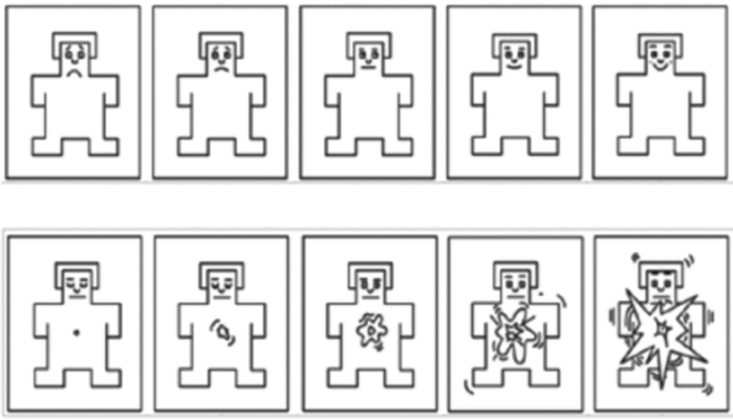

Figura 1. The Self-Assessment Manikin (SAM) used for affective labeling. The top row illustrates valence (unpleasant to pleasant), and the bottom row illustrates arousal (calm to excited), each rated on a 1–9 scale.

affective labels. This consolidated description highlights the active, task-based nature of EduEmotion and contrasts it with prior datasets such as DEAP or SEED, which rely mainly on passive media consumption.

Tabela 1. Structure of the EduEmotion dataset

Attribute	**Description**
Participants	22 adults (19–48 years, mean = 27.3, SD = 6.9; 13 female, 9 male)
Tasks per session	4 (File navigation, Online search, Spreadsheet manipulation, Arcade game)
EEG device	Emotiv EPOC, 14 saline-based electrodes (10–20 system)
Sampling rate	128 Hz
Signal preprocessing	Bandpass filter (1–50 Hz), automated artifact removal (ocular/muscle)
Trials per participant	4 tasks × 1 session each
Labels	Self-Assessment Manikin (SAM) ratings of valence (1–9) and arousal (1–9), post-task

4. Results and Discussion

The tasks in the pilot study were intended to capture both classroom-like dynamics and the independent, self-regulated aspects of distance education. For instance, the spreadsheet manipulation and online shopping simulation tasks required participants to navigate digital interfaces and complete problem-solving exercises with minimal direct supervision. This setup is analogous to many e-learning environments, where learners must independently manage digital resources and monitor their own engagement (Zhang et al. 2020; Rodríguez et al. 2020).

Participants largely self-managed these tasks, which provided a natural context for observing how attention and engagement fluctuate in the absence of continuous face-to-face oversight. In such settings, EEG-based monitoring may be particularly effective at detecting hidden signs of frustration or waning attention that might otherwise go unnoticed in remote learning scenarios. Our preliminary EEG analyses indicate that subtle shifts in neural activity during these independent tasks can serve as early indicators of cognitive or emotional challenges, thereby suggesting opportunities for timely intervention.

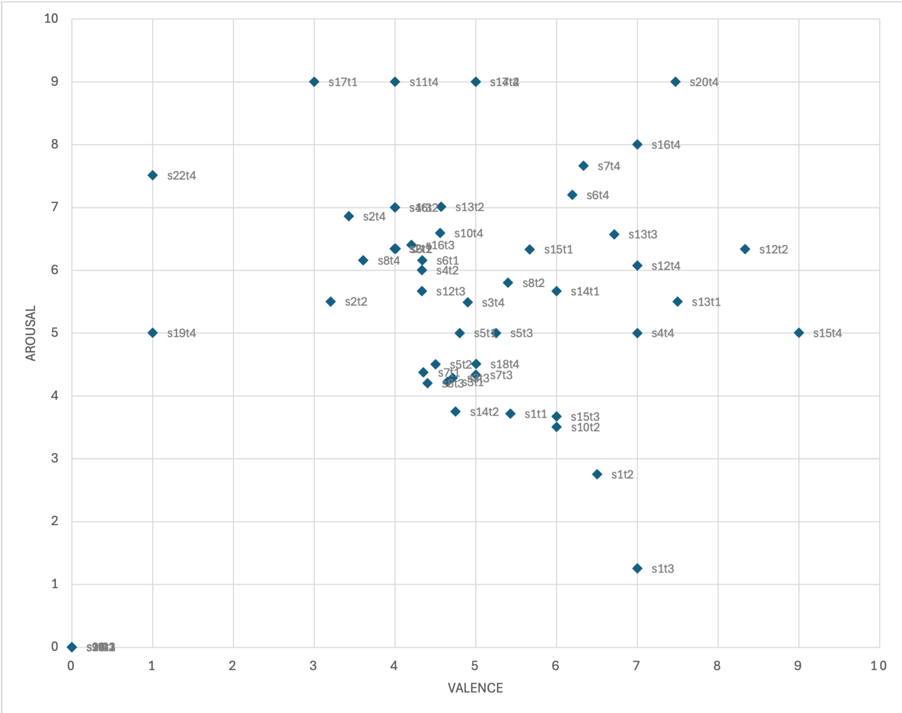

Figura 2. Self-reported valence and arousal scores across all tasks and participants.

Figure 2 summarizes the distribution of affective self-assessments across all tasks in the valence-arousal space. Most responses clustered between valence scores of 3 to 8 and arousal scores of similar range, suggesting that the designed tasks elicited a rich but bounded spectrum of emotional experiences. This concentration is particularly relevant for distance education contexts, as it reflects moderate-to-high arousal levels and mixed valence—a combination often associated with productive tension, cognitive effort, and active engagement. By avoiding extremes (e.g., very low arousal or extremely negative valence), the dataset mirrors typical emotional states encountered during self-guided study or timed online activities, reinforcing its ecological validity for emotion-aware educational technologies.

These findings support the potential of EEG systems to complement existing online educational tools by providing real-time feedback that could alert instructors or adaptive software when learners begin to disengage. In environments where students interact primarily through digital platforms, the ability to monitor and respond to affective states could help bridge the gap caused by the lack of immediate, in-person observation.

These patterns were further contextualized by participant feedback. A brief post-task questionnaire revealed that most users found the Emotiv EPOC headset tolerable for 20–30 minutes of use and that its lightweight design facilitated ease of use.However, occasional challenges with maintaining consistent electrode contact occurred on participants with thicker or denser hair. In these cases, slight readjustments were needed during longer tasks such as file navigation and the online shopping simulation, where continuous interaction sometimes led to minor disruptions in signal quality. Conversely, shorter-duration tasks like the arcade game segment were generally rated as more comfortable, with fewer interruptions reported.

Some users also noted that, while the headset was not overly intrusive, there were brief moments of discomfort when electrode contact was suboptimal. These observations suggest that further refinements in electrode design or calibration protocols could enhance overall user comfort, particularly for extended sessions in real-world educational settings.

In summary, despite minor issues related to electrode contact, the feedback from participants indicates a generally positive reception. This suggests that, with incremental improvements, EEG-based emotion recognition systems can be effectively integrated into both traditional and distance learning environments.

5. Conclusion and Future Work

Emotions are central to learning, influencing motivation, engagement, and performance. While affective computing has made substantial progress (Picard, 1997; D'Mello & Graesser, 2021; Holmes & Bialik, 2019), there remains a lack of ecologically valid EEG datasets that reflect educational contexts. Existing datasets such as DEAP and SEED are based on passive media consumption (videos or films), which does not capture the dynamics of active, task-based learning. EduEmotion addresses this gap by providing EEG and affective self-reports collected during cognitively meaningful, domain-neutral tasks.

Our primary goal was to build a dataset that could represent the emotional landscape of learners engaged in self-guided or instructor-led digital tasks — without anchoring these tasks in specific course content, academic disciplines, or subject matter. This neutrality was intentional. We wanted the dataset to be usable by educational researchers regardless of whether their focus was on mathematics education, literacy interventions, STEM support, or broader digital learning environments. By designing tasks such as file navigation, online search, spreadsheet manipulation, and simple gameplay, we prioritized functional cognitive challenges over disciplinary knowledge.

This design choice also allowed us to recruit participants from diverse academic backgrounds and skill levels, simulating the heterogeneity of real classrooms or distance education cohorts. As a result, emotional responses — as captured via self-report and EEG signals — emerged not from content familiarity, but from interactional elements like time pressure, interface navigation, or problem-solving load. This is particularly important for educational equity: systems that adapt to emotional states should be responsive to learners' experiences, not their prior exposure to specific knowledge domains.

In addition, we emphasized privacy-aware data handling. Raw EEG recordings were discarded immediately after feature extraction to minimize risk and to align with ethical frameworks for biometric data collection. We also gathered feedback on device comfort and task accessibility, revealing modest friction with electrode contact but overall acceptance among participants. This supports the viability of using such devices in real-world educational settings, provided that ergonomic refinements continue.

The distribution of valence-arousal scores across tasks further reinforces the realism of our dataset. Most self-reports fell within moderate arousal and mid-to-positive valence ranges — emotional zones that align with cognitive effort, mild frustration, and engagement. This avoids the emotional extremes often induced in laboratory settings and more accurately reflects the affective rhythms of students working through educational materials independently or under light guidance.

The EduEmotion pilot demonstrates the feasibility of capturing emotionally meaningful EEG data during digital tasks that mimic distance education and blended learning scenarios. By avoiding domain-specific content, we created a flexible dataset that can support researchers developing emotion-aware educational tools across a range of disciplines. Our approach also underscores the importance of ethical design: minimizing data retention, anonymizing signals, and ensuring user comfort are not peripheral concerns — they are essential for scalable, responsible deployment.

In future iterations, we aim to expand this dataset with additional tasks, longer sessions, and more diverse participant profiles. We also plan to explore integration with other modalities, such as eye tracking or keystroke dynamics, to improve robustness. Real-time dashboard interfaces, teacher-facing feedback systems, and longitudinal trials in real classrooms are all in scope for follow-up studies.

We also recognize that emotion recognition in education must go beyond detection — it must inform action. Therefore, a crucial next step will be prototyping adaptive mechanisms that respond to signs of disengagement or frustration in ways that are pedagogically meaningful and ethically sound.

With sustained collaboration among educators, data scientists, and ethicists, we envision that EEG-based emotion recognition can become a potent ally in tailoring education to meet individual learner needs. By combining robust neural monitoring with adaptive instructional strategies, future educational systems can offer more personalized, empathetic, and effective learning experiences.

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