

EEG-Based Brain-Computer Interface for Educational Games: Cognitive State Monitoring in AI-Driven Financial Literacy Learning

Gabriel Machado Santos¹, Rita Maria Silva Julia¹, Marcelo Zanchetta do Nascimento¹

¹Computer Science Faculty - Federal University of Uberlândia
Uberlândia, MG

{gabrielmsantos, rita, marcelo.nascimento}@ufu.br

Abstract. Introduction: Behavioral logs from educational games capture player actions but not the cognitive states underlying decisions. EEG complements these logs by providing continuous measures of attention and affect. **Objective:** We present a feasibility study integrating an Emotiv EPOC X (14-channel) EEG headset with a Unity 3D financial literacy game for two purposes: BCI-based game control through mental commands and passive monitoring of six cognitive metrics—Interest, Excitement, Stress, Engagement, Relaxation, and Attention—synchronized with AI advisor interventions. **Methodology:** We implemented a Unity–Emotiv Cortex SDK pipeline and evaluated six children in two sessions: a BCI Control Session, using four mental commands (Left, Right, Push, and Idle), and a Cognitive Monitoring Session, in which EEG metrics were passively synchronized with in-game AI advisor events. **Results:** Preliminary results show alignment between EEG-derived cognitive states, player decisions, and self-reports. Stress increased during gambling events and remained stable after investment decisions consistent with AI guidance, demonstrating the feasibility of integrating EEG into educational games and motivating future multimodal adaptive learning systems. **Keywords** Brain Computer Interface, EEG, Educational Games, Financial Literacy, Cognitive State Monitoring, Adaptive Learning

1. Introduction

Behavioral logs — click patterns, decision sequences, response times — have been the primary signal for adaptive educational systems and knowledge tracing [VanLehn 2011]. These logs are inherently indirect: they reveal *what* a player did, but not the cognitive or affective state driving that decision. A child who ignores an AI advisor’s investment tip and gambles instead may be inattentive, cognitively overloaded, or deliberately experimenting — states with entirely different pedagogical implications that behavior alone cannot disambiguate.

EEG provides a complementary, continuous, physiological signal. Consumer-grade headsets have lowered the barrier to field deployment [Ramirez e Vamvakousis 2012], yet most EEG-in-education work targets adult participants in static video-watching or reading tasks [Pei et al. 2025, Apicella et al. 2022], not interactive games with children and embedded AI systems.

This paper reports a feasibility study integrating the Emotiv EPOC X with John and the Rainbow Coins (JRC)¹ [John and the Rainbow Coins Project 2026] a 2D financial literacy game for children aged 7–12 featuring a Quality-Diversity GenAI advisor. Our dual contribution: (1) BCI-based game control via four trained mental commands as a novel interaction modality, and (2) passive EEG performance metric capture timestamped against in-game AI advisor events. We demonstrate technical feasibility and provide an honest account of practical deployment challenges.

2. Related Work

EEG has been used as a passive sensor for cognitive load and engagement in education. Pei et al. [Pei et al. 2025] validated EEG tracking of cognitive load during video-based learning, while Apicella et al. [Apicella et al. 2022] demonstrated continuous neural monitoring of student engagement in classroom settings. Consumer EEG devices have been validated for affective state classification in HCI contexts [Ramirez e Vamvakousis 2012], though predominantly with adult, static-task populations.

In games, BCI control has focused on motor-impaired users and rehabilitation serious games [Müller et al. 2003, Lotte et al. 2013]. Bellotti et al. [Bellotti et al. 2009] and Plass et al. [Plass et al. 2015] called for multimodal physiological monitoring in serious games evaluation and adaptive game design, respectively. To our knowledge, no prior work combines real-time EEG monitoring with an AI-driven adaptive advisor in an educational game deployed with children — the gap this work addresses.

3. System Architecture

3.1. The Educational Game

JRC is a 2D Unity 3D platformer teaching financial literacy through coin collection, investment, credit, gambling, and spending decisions. A Quality-Diversity multi-agent GenAI advisor delivers real-time personalized guidance based on an 8-dimensional player state vector [Machado Santos et al. 2026]. This advisor is the pedagogical mechanism whose cognitive impact we aim to monitor via EEG.

3.2. EEG Device and Performance Metrics

The Emotiv EPOC X provides 14 electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4; references CMS/DRL at P3/P4). We used the Emotiv Pro Performance Metrics module, which derives six normalized $[0, 1]$ state estimates at ≈ 8 Hz: **Interest** (attraction/aversion to stimuli), **Excitement** (reaction intensity), **Stress** (emotional tension), **Engagement** (task immersion), **Relaxation** (calm focus), and **Attention** (sustained focus). All metrics were logged with Unix timestamps for synchronization.

3.3. Unity–Emotiv SDK Integration

As illustrated in Figure 1, we developed a C# plugin interfacing Unity with the Emotiv Cortex SDK via WebSocket API. The integration supports two data streams used in *separate* experimental sessions (A demonstration video is available²):

¹<https://johnandtherainbowcoins.com/>

²<https://www.youtube.com/watch?v=uDGoNObOB0A>

Session A — BCI Game Control. Each participant trained four mental commands using the Emotiv Mental Command interface: *Right* (move right), *Left* (move left), *Push* (jump), and *Idle* (neutral state), requiring approximately 8 repetitions per command. During this session, the headset acted exclusively as a control input device.

Session B — Cognitive State Capture. In a separate session, the Performance Metrics stream was captured continuously during standard keyboard-controlled gameplay and written to a timestamped CSV log alongside the Unity game event log. A shared epoch timestamp at session start enabled post-hoc alignment of EEG states with specific game events (advisor tip shown, investment made, gambling attempted, etc.). This design avoided the confound of dual cognitive load from simultaneous BCI operation and financial decision-making.

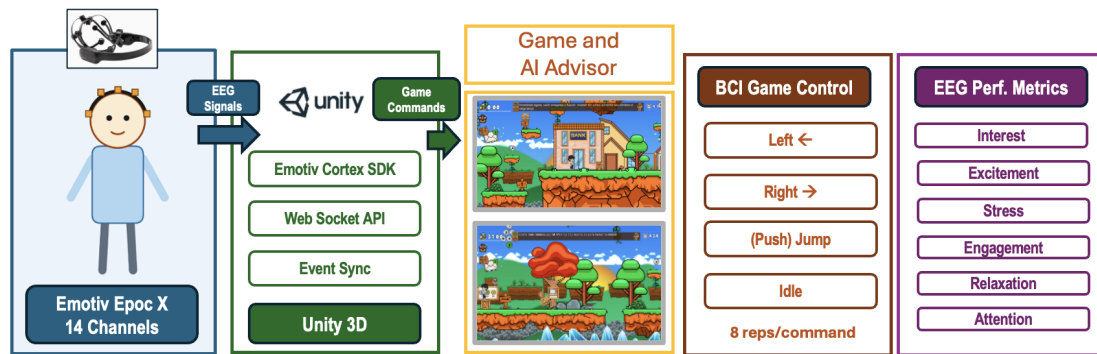


Figure 1. System architecture: child participant wearing the Emotiv EPOC X (14 channels) connects via the Emotiv Cortex SDK WebSocket API to a C# Unity plugin. The two streams were collected in separate experimental sessions: Session A for BCI game control and Session B for passive cognitive state monitoring, avoiding the confound of concurrent BCI operation and financial decision-making. .

4. Feasibility Study

4.1. Participants and Protocol

Six children (aged 8–12; 3 female) voluntarily participated in the project, all with prior game experience from an earlier study phase. Ethics Committee approval was obtained (CAAE: 78520523.0.0000.5152); parents/guardians provided informed consent.

Each participant completed two sessions: (1) *BCI Control Session*: headset fitting and signal quality check (≈ 10 min), followed by mental command training (≈ 8 min per command) and BCI-controlled gameplay (15 min); (2) *Cognitive Monitoring Session*: headset fitting, passive EEG metric capture during standard keyboard-controlled gameplay with AI advisor active (15 min), and a brief qualitative interview. Sessions were conducted individually on separate days due to single-device constraints.

4.2. Data Collected

Session A yielded BCI command recognition logs per participant. *Session B* yielded: (a) EEG performance metric stream (6 metrics $\times \approx 8$ Hz, timestamped); (b) Unity game event log (decisions, advisor events, financial outcomes); (c) post-session qualitative report. Session B logs were aligned via shared epoch timestamp.

5. Preliminary Results

BCI Control (Session A). All six participants operated BCI control during gameplay, though with varying reliability. Participants with more training repetitions achieved higher command recognition rates. Two participants showed recognition rates below 60% for directional commands, reflecting known individual BCI aptitude differences [Müller et al. 2003]. Unanimously, participants expressed high enthusiasm for the modality (*“It is so cool that the game knows what I’m thinking”*), suggesting a strong novelty engagement effect.

Cognitive State Dynamics (Session B). Figure 2 shows representative EEG traces for one participant. Attention and Engagement show transient increases coinciding with AI advisor events. Stress diverges by the player’s subsequent action: it rises sharply when the player ignores the advisor and gambles, and remains low or shows a mild dip after investment decisions aligned with the advisor. Participant self-reports corroborated these patterns — one child described feeling pressure *“when the advisor warned me about gambling but I still wanted to try”*. These results constitute preliminary evidence of methodological feasibility, not statistical inference.

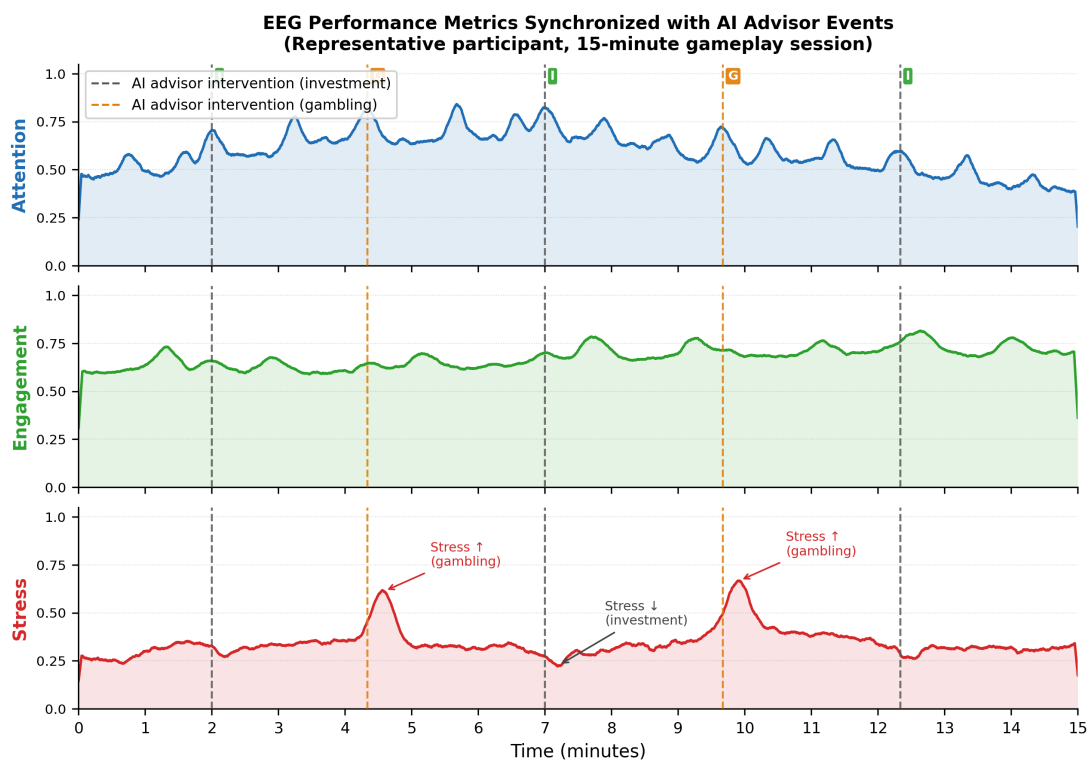


Figure 2. Representative EEG performance metric traces (Attention, Engagement, Stress) for one participant synchronized with AI advisor events. Dashed lines mark advisor interventions; orange = gambling outcome, grey = investment outcome. Stress diverges by post-intervention decision.

Game Performance Alignment. Participants with higher session-average Engagement tended toward better financial outcomes (fewer gambling events, more investments). Attention followed a non-monotonic pattern: moderate levels correlated

with optimal decisions, while very high levels often preceded platform errors, likely reflecting the cognitive overhead of concurrent BCI operation.

6. Challenges and Lessons Learned

Table 1 summarizes the key deployment challenges and proposed mitigations. Reporting them explicitly is itself a community contribution, given how rarely BCI field studies with children are documented.

Table 1. Deployment challenges and mitigations.

Challenge	Mitigation
Cost & import taxes	Lower-cost headset (e.g., Muse S)
Calibration (~10 min)	Calibration mini-game
Motion/EMG artifacts	Real-time filtering in Unity
4-command training	Transfer learning
Single-device use	Two-device scheduling
BCI aptitude	Keyboard fallback

7. Conclusion

This study demonstrates the feasibility of integrating EEG-based cognitive monitoring with a BCI-controlled AI-driven educational game for children. The dual role of BCI—as both control interface and cognitive sensor—produced signals that aligned with gameplay events and self-reports. We also identify practical deployment challenges, including device cost, calibration, child mobility, scalability, and training burden.

Separating BCI control from passive EEG monitoring into distinct sessions intentionally avoided the dual-task confound, providing a foundation for future studies that integrate both simultaneously.

A promising next step is to condition LLM-Augmented Knowledge Tracing on EEG-derived attentional states, enabling the distinction between children who genuinely understand a financial concept and those who make correct decisions while cognitively disengaged.

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