EMIGC: An EEG Motor Imagery Controller for Real-Time Gameplay

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Abstract. This study verifies that a consumer-grade five-channel EEG headset can, through a unified real-time decoding pipeline, deliver reliable directional control across different game genres. We introduce the **EEG Motor Imagery Game Controller (EMIGC)**. Muse 2 signals undergo standard preprocessing and sliding-window segmentation before entering a lightweight CNN-LSTM that decodes three sustained states and six transitional states, which are mapped to left/neutral/right commands. The same model seamlessly drives three Unity prototypes—*Hide and Seek*, *Snake*, and a two-lane *Rhythm* game, while multimodal feedback enhances the user experience. An event-based logger and a Formula Score provide fine-grained performance analysis, and questionnaire results indicate positive usability and immersion. EMIGC runs stably in all prototypes, demonstrating the feasibility of consumer-grade EEG for real-time, cross-genre game control.

Keywords: Brain-computer Interface System · Motor Imagery · Electroencephalography (EEG) · real-time gameplay · BCI games · EEG signal classification · game design

1 Introduction

Electroencephalogram (EEG)-controlled gaming is an emerging field that enables direct brain–computer interaction by translating neural activity into real-time control commands. In particular, motor imagery (MI)—the mental simulation of movement without physical execution—has gained prominence as a non-invasive neural correlate of motor intention. Advances in artificial intelligence have significantly improved the decoding of MI-related EEG patterns, enabling recognition of a user's intended motor action. However, achieving real-time game control using EEG signals remains a unique challenge, requiring low-latency signal processing, robust machine learning algorithms, and game design paradigms that are compatible with the constraints of brain-based input.

This experiment investigates the feasibility of using an EEG-Motor Imagery Game Controller(EMIGC) system. The EMIGC system integrates signal processing and robust machine learning models with performance evaluation as a game controller. This system aims to optimize algorithmic performance and user experience.

1.1 Research Question

- **How can EEG signals be sampled and processed to enable accurate directional control in real-time gameplays?**
- **Can we develop a framework for MI-BCI games?**

1.2 Game's Mass Appeal

To ensure broad appeal and inclusiveness, we designed three EEG-controlled games across different genres: a classic Snake game, a rhythm-matching game, and a playful hide-and-seek scenario. These games were chosen for their intuitive controls, low cognitive load, and suitability for diverse demographics.

We utilized consumer-grade EEG headsets for accessibility and ease of use, accepting a trade-off in signal fidelity. These devices offer lower cost, simpler operation, and faster setup compared to research-grade alternatives [29]. Multimodal feedback—including visual and auditory cues—was integrated to enhance immersion and motivation, aligning with research showing its benefits in BCI interaction. Our design prioritizes fast onboarding, diverse engagement, and real-time playability in non-lab environments.

1.3 Limitations in Current BCI Game Design

Although MI-based BCI games are technically feasible, many suffer from constrained gameplay mechanics and minimal interactivity, as they are often developed primarily for algorithm validation rather than user experience [10]. Evaluations typically rely on classification accuracy or in-game scores, which fail to isolate BCI performance due to various confounding factors. Distractions and mental fatigue further affect users' ability to perform consistent motor imagery. Prior reviews highlight that well-designed, engaging gameplay can enhance both user focus and control accuracy over time.

Our system is informed by these findings, aiming to improve game diversity, reduce cognitive load, and support real-time responsiveness without requiring long training phases.

2 Related Work

EEG-controlled games have gained increasing attention as BCI technology matures [2, 3, 11, 16, 17, 28–30]. Most studies focus on motor imagery (MI)-based directional control, employing deep learning models such as CNNs and RNNs to improve classification accuracy[4, 1]. However, due to the high variability and noise of EEG signals, real-time reliability remains a key challenge [31].

To address these signal issues, various EEG preprocessing and feature extraction pipelines have been explored. A typical pipeline involves band-pass filtering (e.g., 1–50 Hz) to remove low-frequency drift and high-frequency noise, followed by normalization such as per-channel z-scoring to reduce inter-subject variance.

After preprocessing, data is often segmented using sliding windows to generate training samples for classification models [8].

Feature extraction plays a key role in improving model efficiency and generalizability. For instance, Li et al. [14] applied power spectral density (PSD) and differential entropy (DE) across five canonical EEG bands (delta to gamma), followed by statistical channel selection. This approach reduced dimensionality from 290 to 45 while preserving discriminative power, enabling real-time performance.

There is an ongoing trade-off between time-domain deep learning approaches and frequency-domain feature engineering. While CNN-based models can extract spatial-temporal patterns directly from raw signals, they often require large datasets and computational resources. Frequency-based methods offer interpretability and efficiency but may sacrifice some temporal resolution. Hybrid architectures such as CNN+LSTM remain popular for capturing both spatial and temporal dynamics in EEG data [4, 5, 7, 9, 12, 13, 15, 18–27, 32].

Game-based BCI interfaces have demonstrated improved engagement and precision; a review of 2524 studies found that 26 of 28 reported positive outcomes [10]. Yet, a systematic analysis of 80+ consumer-grade EEG games revealed that most are designed for educational or clinical purposes, with minimal interactivity and long training durations[29]. Devices like NeuroSky and Emotiv are commonly used in "serious games," with little focus on gameplay quality or fast response. Common limitations include low control granularity, high latency, and poor support for MI or emotion-based inputs.

These observations align with recent perspectives advocating for novel interaction paradigms tailored to BCI constraints, rather than imitating traditional input methods [6]. Our EMIGC system responds to this direction by designing game mechanics specifically tailored to the characteristics of MI-BCI interaction, and by employing more reliable analytical methods in the study of MI-BCI games.

2.1 Case Study: Limitations of Tux Racer for BCI Interaction

The open-source nature of Tux Racer, a 3D winter racing game, provides researchers with easy access for BCI integration and data collection. However, it presents several critical limitations for both EEG research and general gameplay.

First, its acceleration-based control system lacks intuitive directional mapping, making it difficult to directly assess input accuracy. Since scoring is based on coin collection, performance is more influenced by route familiarity than by precise control. Additionally, the delayed follow-camera introduces perceptual lag and spatial disorientation, often leading to a disconnect between user input and visual feedback, potentially introducing noise into EEG recordings.

Furthermore, the game's continuous control demand and lack of angular constraints are ill-suited to the high latency and limited precision of EEG inputs. These design mismatches conflict with core BCI experimental principles: reducing cognitive load, minimizing confounding factors, and ensuring a natural mapping between input and system response.

In the following sections, we present the design, implementation, and evaluation of the EMIGC system.

3 Method

3.1 EMIGC System Design

To systematically explore the feasibility and practical constraints of EEG-controlled digital games, we developed a complete interactive system that tightly integrates real-time EEG signal classification with responsive game logic. This system is specifically designed to bridge the gap between raw brain activity and interpretable, game-relevant input commands. We refer to this framework as the **EEG Motor Imagery Game Controller (EMIGC)**, highlighting its focus on decoding motor imagery (MI) signals for in-game directional control. Figure 1 summarizes the structure of the EMIGC system.

EEG Data Acquisition EEG signals were recorded using the Muse 2 headband, which provides 5 channels (TP9, AF7, AF8, TP10, and Right AUX) sampled at 256 Hz. For each participant, data was collected in two sessions: a training session for model fitting, and a real-time session for gameplay testing. Participants were instructed to perform six distinct motor imagery (MI) tasks cor-

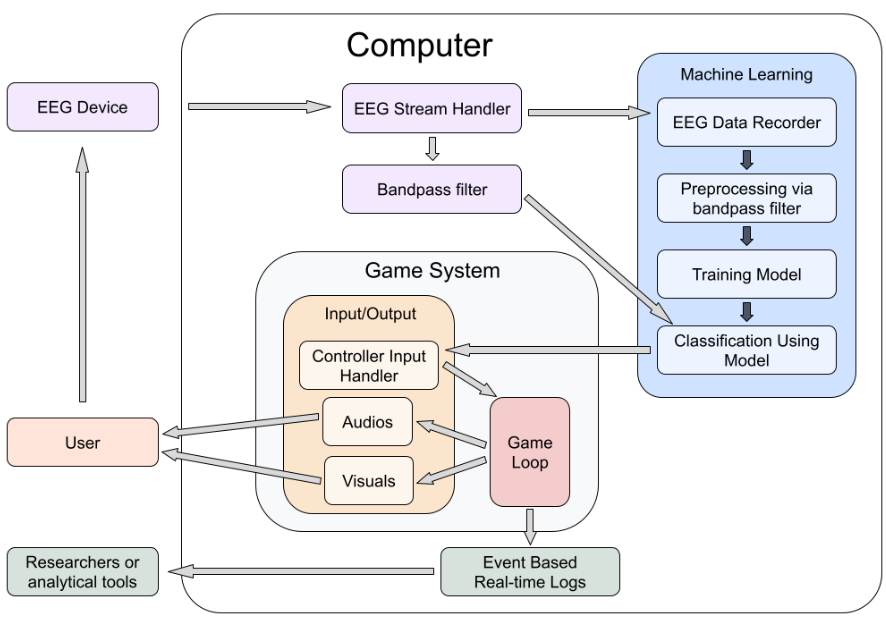

Fig. 1. EMIGC Framework

responding to directional intentions: left-to-middle, left-to-right, middle-to-left, middle-to-right, right-to-left, and right-to-middle.

EEG Data Processing Raw EEG signals were band-pass filtered between 1–50 Hz to remove low-frequency drift and high-frequency noise. Z-score normalization was then applied per channel to reduce inter-subject variance. A sliding window (1000 ms, 256 samples; step 500 ms) was used to generate training segments. Labels were derived from file metadata, and all segments in a file shared a one-hot label.

EEG Data Classification We used a hybrid CNN–LSTM model to classify EEG segments into six directional categories. CNN layers extract spatial patterns across channels, while LSTM layers capture temporal dependencies. The network architecture includes two convolutional blocks (Conv1D, BatchNorm, ReLU, Dropout, MaxPooling), followed by LSTM, a dense ReLU layer, and softmax output.

Game Design and Development To address the design limitations of early EEG games such as *Tux Racer*, which failed to account for the specific constraints of brain-based control, we propose three core design principles: ensuring intuitive control schemes, minimizing cognitive load, and preserving engaging gameplay.

We eliminate unnecessary operations and complex mechanics to reduce external interference, and simplify interaction flow to lower execution difficulty for users. In addition, the system incorporates multimodal feedback (visual and auditory) to enhance the sense of responsiveness and overall immersion. While improving user experience, we also maintain clear and structured command outputs to support stable and reliable EEG signal classification.

Event-Based Real-time Logging To enhance the reliability and depth of EEG data analysis, the EMIGC system adopts an **event-based real-time logging mechanism** during gameplay. Unlike traditional methods that rely solely on game scores or overall accuracy, our system marks and categorizes EEG signals in response to discrete in-game events, including user command issuance, directional decisions, and feedback triggers. This enables more granular evaluation and opens up avenues for future research.

By aligning EEG segments with task-relevant events, this event-driven approach reduces the influence of irrelevant brain activity and minimizes interference in the preprocessing and classification stages. It improves the signal-to-noise

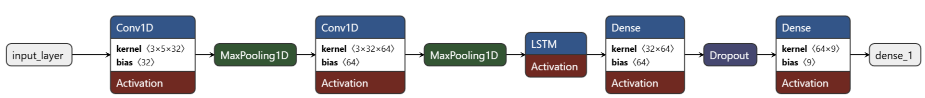

Fig. 2. CNN + LSTM

ratio and supports a more accurate assessment of user intent, response latency, and classification reliability across varying interaction conditions.

Proposed improvements To address the limitations of games like Tux Racer, which fail to consider the specific constraints of EEG-based control, we propose that EEG-compatible games adopt simplified control schemes and avoid non-intuitive or weakly responsive input designs. Additionally, cognitive load should be minimized by removing non-essential gameplay mechanics and streamlining interaction logic.

Our goal is to lower the learning curve, making directional control accessible even to users with limited gaming experience. To enhance user engagement without compromising EEG signal quality, we incorporate visual and auditory feedback designed to reinforce the sense of interactivity and immersion, while minimizing the impact on EEG signal classification.

4 Result

Based on the EMIGC framework, we designed three EEG-controlled games specifically tailored for motor imagery-based BCI interaction. These games follow a consistent set of design principles: clear and minimalistic mechanics, turn-based structure to accommodate EEG classification latency, and left/right/neutral directional control.

Each game is designed to be inclusive and accessible to users across different age groups and genders, emphasizing intuitive interactions and low cognitive load. Below, we describe the three games in detail.

Since the Unity Engine is widely used in other studies and is renowned for its user-friendliness and helpful community. To stream inputs from EEG classifier to the games, we used Python's pynput.keyboard library to generate keyboard inputs based on classified results.

Hide and Seek Game In this game, the player engages in a hide-and-seek interaction with a child character. The player remains fixed at the center of the

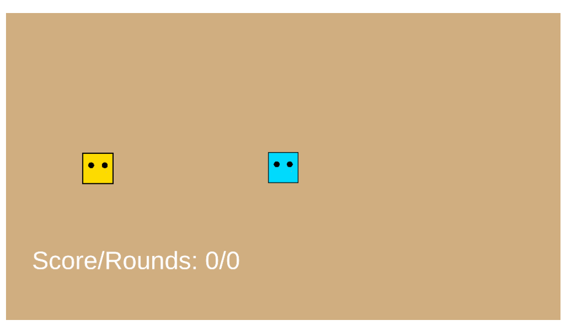

Fig. 3. Hide And Seek Game

screen, while the child appears intermittently on either the left or right side. The player must move in the direction of the child within a limited time to "catch" them. This theme makes the game suitable for players of all ages, including children and adults.

In terms of gameplay design, the Hide and Seek game is intuitive and straightforward, requiring only left and right directional movements. Players simply need to respond to the position of the child, making the game easy to understand and accessible even for users with no prior gaming experience, making it particularly suitable for research purposes. To enhance visual appeal, dynamic animations such as body movement and jumping effects were added during character transitions. Additionally, the child's visual design clearly indicates their location, helping users quickly identify the correct target direction.

Figure 3 shows the Hide and Seek game, where for each round a child will appear on the left or the right side of the screen, and the player has to move the avatar from the middle to catch the child.

Snake Game Design Rationale We selected the classic **Snake** game as one of our experimental games due to its simple rules and wide familiarity, allowing players to quickly understand and engage with the gameplay without requiring additional instructions. Players control the snake to move left, right, or straight in order to eat food and grow longer. Based on this intuitive mechanic, we further optimized the game's presentation and system interaction to enhance user experience under EEG control.

To increase engagement and reduce fatigue associated with brain-based input, we adopted a cartoon-style visual design paired with soft sound effects. This not only improves the game's appeal but also avoids interference with EEG signal quality. Given the $\tilde{1}$-second latency in EEG signal recognition, food generation was made controllable. This ensures that delayed inputs do not penalize the player by missing targets, thereby enhancing fairness and evaluation reliability in EEG-controlled conditions.

Additionally, we introduced several gameplay optimizations to improve fault tolerance and playability: (1) the snake no longer dies upon colliding with itself, offering players more movement freedom; (2) when hitting the screen bound-

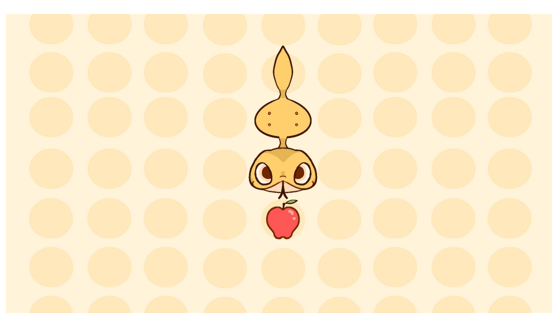

Fig. 4. Snake Game

ary, the snake now turns 180 degrees instead of wrapping around, providing more intuitive spatial feedback. These adjustments reduce operational stress, help maintain player focus, and create a clear and reliable environment for evaluating EEG-based directional control.

Rhythm Game Falling-style rhythm games are well-suited for studying directional control input in BCI systems due to their **engaging gameplay, unit-test-like structure, strong rhythmic alignment**, and compatibility with **left-right binary input** when simplified to a dual-lane format. In this game, notes on the track will fall with the rhythm of the song. When a note enters the detection zone, the player will give the correct directional input to fulfill the note and get the points from the note.

Unlike traditional 4-track, this game is tailored for a bi-directional control task. When the player performs wrong actions, there's no punishment except that the combo counter will be reset, and the player cannot score the point of that note. Missing a note is not a punishment, but the combo counter is a sunk cost during a gameplay session, which means that the will to keep the combo count is the driving force of the player to get more accurate inputs.

To accommodate EMIGC's relatively high latency and variable accuracy, the game employs soothing, melodic music and abandons the traditional rhythm-game approach of strict beat-based note timing. Instead, each track allows players to register a correct input anywhere within a given bar. This design also makes the game accessible to a wider audience, including those with no prior experience in rhythm games.

4.1 Performance Metrics

Quantitative Approach Quantitatively, we used classification accuracy, score, and skill score to evaluate the performance of EMIGC. Classification accuracy directly assesses the effectiveness of EEG signal classification, and score is a simple yet intuitive way to evaluate how well the subjects play the games. However, the discreteness of the score prevent us from precisely measuring the subjects' controllness and skill while playing the game. For example, in the Hide And Seek

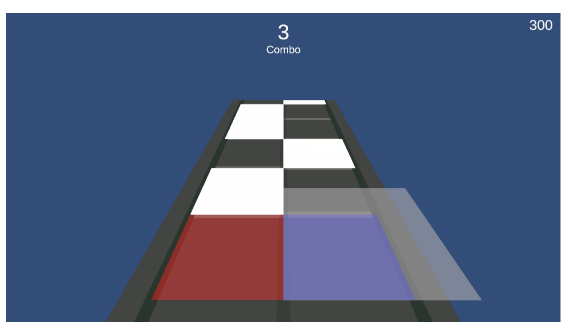

Fig. 5. Rhythm Game

subject A is very close to catch the child, whereas subject B cannot get close to the child at all. Both subjects get a score of 0, but obviously subject A is better at playing the game. The event-based real-time logging mechanism ensured that researchers could analyze every detail of the game state during the test. Therefore, the skill score is used to more precisely measure how well a subject performs in the games. Table 1 shows the definition of the metrics for each game.

- **Hide And Seek:**
$$\frac{1}{n}\Sigma_{i=1}^{n} x_{max} \cdot \bar{v}$$
Because Hide and Seek emphasizes sustained correct input, its formula score is defined as the cumulative amount of correctly executed directional controls. Even if the player never reaches the child, each correct maneuver still contributes to increasing their score. . n is the number of rounds played. Within a round, x_{max} is the maximum distance the player has walked toward the child divided by the player's initial distance from the child. The division guarantees that x_{max} is normalized between 0 and 1. $\bar{v}$ is the average velocity of the player over the round. $\bar{v}$ is normalized between 0 and 1. The final output of this formula is a real number between 0 and 1, with 1 indicating complete control over the avatar, 0 indicating no control over the avatar.
- **Snake Game** The composite scoring formula is designed to reflect the overall quality of EEG-based control, rather than relying solely on raw gameplay outcomes. Traditional metrics, such as the number of food items collected, provide limited insight into the precision, consistency, and responsiveness of the user's mental commands. In contrast, the proposed formula incorporates multiple dimensions of control performance that are critical in BCI contexts.
$$\text{Snake Score} = \frac{1}{n}\sum_{i=1}^{n} \frac{f_i}{f_{\max}} \cdot \bar{v}_i \cdot \left(1 - \frac{s_i}{s_{\max}}\right)$$
Specifically, the number of food items collected ($\frac{f_i}{f_{\max}}$) serves as an indicator of task completion efficiency, while the average movement velocity ($\bar{v}i$) captures the user's ability to maintain continuous and stable control. To assess

Table 1. Definition of quantitative metrics for each game

Game	**Definition of Score**	**Formula to Calculate Skill Score**
Hide and Seek	number of children caught	$\frac{1}{n}\sum_{i=1}^{n} x_{\max}\,\bar{v}$
Rhythm Game	number of notes hit	$\frac{1}{\lvert X\rvert}\sum_{\substack{x\in X\\ x_{\text{correct}}=1}} \left(1 - \frac{x_{\text{opp\_time}}}{x_{\text{dir\_time}}} - \frac{x_{\text{res\_time}}}{x_{\text{window}}}\right)$
Snake Game	composite score of food and movement	$\frac{1}{n}\sum_{i=1}^{n} \frac{f_i}{f_{\max}}\,\bar{v}_i\left(1 - \frac{s_i}{s_{\max}}\right)$

signal clarity and decision-making precision, the formula penalizes excessive directional changes by including a switch count term $\left(1 - \frac{s_i}{s\max}\right)$, which reflects the number of directional switches made before successfully collecting each food item.

All components are normalized to ensure the final score remains within a 0 to 1 range, facilitating meaningful comparison across participants and experimental conditions. This scoring structure provides a more nuanced and reliable measure of EEG control quality, aligning with the experimental goal of evaluating system responsiveness and user adaptability under real-time constraints.

– **Rhythm Game:** The Formula Score (FS) for the rhythm game is designed to reflect the user's ability to control the game. Because the Rhythm Game requires correct inputs within precise timing windows rather than random actions, the core design of its formula score penalizes incorrect operations made during attempts to achieve correct results and awards quick responses. X It is the set of all samples. x It is a single sample X. This x_{dir_time} is the accumulated time on correct input. This $x_{\text{opp\_time}}$ is the accumulated time on incorrect input (not including rest state). This x_{window} is the duration during which input is allowed for the note in this sample. $x_{response\_time}$ It is the time between when the input is allowed for the note in this sample and the moment the required input is fulfilled.

$$\text{FS} = \frac{1}{|X|} \sum_{\substack{x \in X \\ x_{\text{correct}}=1}} \left(1 - \frac{x_{\text{opp\_time}}}{x_{\text{dir\_time}}} - \frac{x_{\text{res\_time}}}{x_{\text{window}}}\right) \tag{1}$$

Compared to the previous two formulas, this formula introduces penalties for incorrect inputs and time, which can lead to negative values under certain conditions.

4.2 Questionnaire

After completing EEG model training and gameplay, participants were asked to complete two subjective questionnaires to assess the system's usability and overall game experience:

– **System Usability Scale (SUS):** Measures the usability and user satisfaction of the system, with a score ranging from 0 to 100.
– **Game Experience Questionnaire (GEQ):** Evaluates the gaming experience across seven dimensions: competence, immersion, flow, tension, challenge, negative affect, and positive affect.

The scores from these questionnaires serve as preliminary qualitative indicators for evaluating the playability and user acceptance of the games developed under the EMIGC system.

5 Discussion

Despite achieving promising directional control, several limitations remain. Real-time EEG signal processing and classification demand considerable computational resources, and reducing the required training time is essential for improving user experience.

Future work will focus on extending the EMIGC system to a broader range of games, optimizing the EMIGC game design paradigm, improve models, shorten training time, and enhancing artifact reduction and adaptive learning to improve system efficiency and user engagement.

All participants in this study remained anonymous, and no unrelated personal data were collected or stored, ensuring full compliance with research ethics and minimizing confidentiality risks.

These improvements are crucial steps toward making BCI-based gaming a viable, scalable, and user-friendly technology.

5.1 Limitations and Future Work

Although our system has demonstrated the feasibility of EEG-based directional control, several challenges remain.

The system still requires a relatively long and tedious training process. This poses a significant entry barrier for new users, and the fatigue accumulated during the training process is a negative factor for user experiences and in terms of EEG-signal quality.

To improve the EEG data–acquisition process during model training, future systems could integrate the EEG training workflow into a game engine (e.g., Unity), offering more intuitive and interactive guidance to lead users through mental tasks. At the same time, the system would provide real-time visualization of the EEG signals as feedback while the tasks are being performed.

To reduce training and calibration time, event-based real-time logging can be used to have a dedicated worker thread pull buffered gameplay samples, run an online learning algorithm, and push the updated model back to the game. This lets EMIGC-based games support a relatively steep difficulty curve, granting designers far greater creative freedom.

However, several limitations emerged during implementation. The system has a roughly 1-second delay between EEG signal classification and game response, which negatively impacts real-time gameplay experience. Additionally, because of its technical limitations, it is also limiting genre diversity. The use of `pynput` for simulating keyboard input, while convenient, may lead to inconsistent behavior across operating systems and lacks robustness for long-term deployment.

Connection via Blue Muse is not stable and makes the player really frustrated when it loses connection and stops streaming. In the future, it is necessary to ask for access to the Muse headband SDK.

6 Conclusion

We asked whether consumer-grade MI-EEG can (i) yield reliable real-time game commands and (ii) do so with a single pipeline that transfers across genres. To answer this question, we built EMIGC, pairing a five-channel Muse 2 headset with minimal preprocessing, a CNN-LSTM decoder, and event-based logging. Demonstrations on three Unity prototypes showed that the same trained model converts six MI classes into stable left/neutral/right actions, and initial SUS/GEQ ratings confirmed positive user experience. These findings provide preliminary evidence that low-cost hardware and brief calibration already suffice for coarse yet usable BCI control. Reducing the current 1-second latency, proving the training process, and hardening the data link are our next targets on the path from demo to mainstream use.

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