Accessible EEG Game Control: Real-Time Personalization with Consumer-Grade EEG Hardware

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Abstract. Personalization remains a major challenge in brain-computer interface (BCI) gaming, where one-size-fits-all thresholds often fail to capture individual variability in EEG signals. This paper presents a real-time EEG-controlled implementation of an open-source game, enhanced with user-specific threshold calibration and adaptive feedback. Using the low-cost Muse S EEG headband, our system maps directional motor imagery to in-game controls (left, right, idle) through a five-stage pipeline: signal acquisition, preprocessing, feature extraction, offline calibration, and real-time decision-making. In a study with fifteen undergraduate participants, two-thirds demonstrated improved directional control following personalized calibration. Participants also reported high engagement and usability. These findings show that personalized real-time interaction is feasible using consumer-grade EEG devices. This work contributes a replicable framework for accessible BCI gaming and offers practical guidance for developers building EEG-based interactive systems.

Keywords: brain-computer interface · EEG-based game control · motor imagery · personalization · threshold calibration · real-time interaction · consumer-grade EEG · adaptive feedback

1 Introduction

Brain-computer interfaces (BCIs) enable users to interact with digital systems using neural activity, offering new possibilities beyond traditional input methods. While BCIs have historically been developed for clinical and assistive purposes, they are increasingly gaining relevance in consumer-oriented domains such as gaming and virtual reality. These emerging applications demand not only reliable control but also engaging, personalized user experiences that adapt to individual variability in brain signals.

This paper presents a real-time EEG-controlled version of the open-source game Tux Racer, enhanced with two personalization strategies: (1) a pre-game calibration step that adjusts left–right EEG control thresholds based on user-specific signal profiles, and (2) a real-time feedback loop that responds to gameplay performance. To our knowledge, this is the first study to adapt a widely available, mainstream open-source game for EEG-based control using both strategies.

Unlike prior BCI research that focuses on custom-built games or fixed control rules, our system introduces a replicable pipeline that combines real-time EEG interaction with pre-session personalization. The system is built using the Muse S headband, a low-cost consumer-grade EEG device, and is designed to be accessible to developers and researchers without specialized biomedical training.

To support this contribution, we conduct a focused literature review on EEG-controlled games and assistive systems. While many existing approaches explore EEG-driven control, few incorporate real-time personalization within open-source or widely used gaming environments. Our system addresses this gap by demonstrating that reliable and engaging interaction is achievable when personalization is applied from the outset.

This work aims to serve as a proof of concept for accessible EEG-based game control and to highlight how user-specific adaptation can improve usability, engagement, and control accuracy.

Ethics Statement: All participants provided informed consent prior to the study. The research protocol was reviewed and approved by the university's Institutional Review Board (IRB), ensuring compliance with ethical standards for human subject research and data privacy.

This paper makes the following contributions:

- A real-time EEG-controlled version of Tux Racer integrating pre-session threshold calibration and real-time performance-based feedback;
- A focused review of EEG-based game control systems, identifying the lack of personalization in open-source environments;
- A reproducible design framework and explanation of key neuroscience concepts tailored for interdisciplinary computer science researchers.

2 Related Work

EEG-based brain-computer interfaces (BCIs) have been explored extensively in gaming and assistive control systems. Prior research has covered signal acquisition, classification, and user interaction [2, 3, 5, 6, 10, 18, 9, 20, 31, 34, 27, 23, 7, 19, 16, 50, 35, 37, 43, 41, 40, 42, 52, 36, 55, 11, 54, 30, 46, 13, 38, 26, 25, 39, 21, 51, 1, 12, 14, 47], but relatively few studies focus on personalization and engagement within consumer-grade game environments. This section summarizes representative studies and identifies gaps our system addresses.

2.1 EEG Signals and Game Control Strategies

Different EEG signal types have been utilized for control, including motor imagery, attention-based modulation, and steady-state visual evoked potentials (SSVEP). Liao et al. [21] and Wang et al. [51] used alpha rhythm fluctuations and fractal dimension analysis respectively to assess attention levels during gameplay. Belkacem et al. [5] introduced eye movement and EEG fusion for directional commands in custom games. Malete et al. [23] applied EEG-based control to a 3D racing game using visual stimulus and attention decoding. Sterk [48] demonstrated a Unity-based BCI system using OpenBCI, highlighting a modular pipeline for mind-controlled play. Palumbo et al. [29] examined EEG correlation and movement timing in a motor-imagery-based maze game. Tariq et al. [49] applied SVM-based classification of motor imagery EEG to a maze navigation task. Pfurtscheller et al. [32] introduced a hybrid BCI combining ERD and SSVEP signals for orthosis control via brain-switching. An et al. [4] developed a combined ERP and SSVEP system for VR-based navigation using threshold calibration. Chi et al. [9] proposed a hybrid BCI using motor imagery and intermodulation SSVEP for enhanced control precision. Li et al. [20] investigated tACS-based enhancement of motor imagery and SSVEP-based BCI performance, relevant to improving game control fidelity. Ahmed et al. [1] developed a hybrid EEG-based BCI system for smart games, detecting both attention and relaxation states using CNN and random forest classifiers, contributing to more nuanced control strategies.

2.2 Adaptation and Personalization

Adaptation techniques have gained traction in recent years to address individual variability in EEG signals. Ahn et al. [2] provided a comprehensive review of EEG signal variability and recommended adaptive algorithms for improved performance. Alchalabi et al. [3] proposed using EEG to train attention via real-time neural feedback. Prapas et al. [35] applied fuzzy logic to tune a personalized threshold for EEG attention-based interaction. Ma et al. [22] demonstrated the effectiveness of personalized neurofeedback games for adolescents with ADHD, revealing the promise of tailored interaction loops. Pantförder et al. [30] advocated for accessible neurotechnology design and engagement-focused BCI interaction in participatory game contexts. Pinto et al. [33] proposed a personalized neurofeedback system using individual baselines for working memory enhancement. Pfurtscheller et al. [32] emphasized subject-specific calibration in hybrid BCI systems to switch between control modalities. Saichoo et al. [44] used user-specific parameter tuning to reduce misclassification rates. Souza and Naves [47] provided a scoping review of attention detection using EEG in virtual environments, distinguishing stimulus-driven and goal-directed mechanisms relevant for personalizing BCI interfaces. However, most of these approaches are limited to custom or simplified environments, lacking integration with established open-source games.

Our system builds on these insights by introducing personalized threshold calibration and feedback loops within Tux Racer—an open-source game not previously adapted for EEG control. The personalization is informed by offline data analysis and considers factors such as user fatigue and cognitive state, which are rarely addressed in earlier game-integrated BCI systems.

2.3 User Engagement and Feedback Loops

While accuracy remains a primary performance metric, user engagement is increasingly recognized as essential for sustained BCI interaction. Alchalabi et al. [3] and Wang et al. [51] began incorporating engagement indicators into their evaluations. Plass-Oude Bos et al. [34] explored how feedback mechanisms influence immersion and motivation. Vourvopoulos et al. [50] highlighted the role of BCI in neurofeedback training and game immersion within rehabilitation contexts. Sawangjai et al. [45] reviewed practical limitations of consumer-grade EEG hardware in user-centered BCI studies, emphasizing ease of setup and data quality trade-offs. Glavaš et al. [13] quantitatively evaluated EEG devices for real-time emotion and workload monitoring in gaming. Krigolson et al. [18] validated a mobile EEG platform for cognitive workload tracking, supporting portable real-time feedback. Nouri [28] used EEG and HRV to evaluate immersion in VR, emphasizing affective computing. Xie et al. [53] explored event-related potentials in real-world gaming sessions, highlighting attention, fatigue, and workload signals. An et al. [4] measured immersion and response latency in hybrid BCI VR settings. Pinto et al. [33] and Saichoo et al. [44] reported improved user satisfaction and sustained engagement through adaptive feedback mechanisms. Chi et al. [9] demonstrated a hybrid BCI combining motor imagery and intermodulation SSVEP to enhance immersive control. Li et al. [20] showed that transcranial stimulation can improve BCI performance and possibly engagement. Park et al. [31] developed a robust BCI framework addressing user fatigue and variability in attention-based gaming. Bellos et al. [6] proposed modular design strategies for improving engagement and signal responsiveness in neuroadaptive games. Garcia et al. [12] reviewed EEG-based engagement metrics across VR environments, which informs our approach to feedback loop design. Gong et al. [14] demonstrated EEG-based detection of working memory load in AR gaming tasks, which can support dynamic difficulty adaptation for sustained user engagement.

2.4 Wearable and Mobile EEG Systems

Recent advances in wearable and mobile EEG systems have facilitated real-time BCI applications in more naturalistic settings. Mullen et al. [24] demonstrated a mobile EEG framework capable of real-time artifact rejection and brain state decoding using dry electrode headsets, laying the groundwork for on-the-go BCI interactions. Cannard et al. [8] validated the Muse headset against laboratory-grade EEG systems in auditory and visual ERP paradigms, supporting its reliability for research and game-based use. Heim et al. [15] developed a real-time self-paced motor imagery and execution system using functional neural networks, achieving high decoding accuracy in game-like environments. Kosmyna et al. [17] introduced AttentivU, a wearable system that provides neurofeedback to enhance attention in everyday tasks, illustrating the potential of discreet, continuous engagement monitoring.

These systems enable portable, low-latency feedback loops that are essential for adaptive game control and personalized user experience in EEG-based gaming environments.

We extend this direction by evaluating not only accuracy and response time but also user engagement through a real-time feedback loop. Our adaptive system dynamically responds to user success or fatigue, offering a more engaging and sustainable control experience.

2.5 Summary of Contributions

Table 1. Summary of EEG-Controlled Game Studies (Extended)

Study	Signal	Personal.	Game	Metric
Liao (2012)	Alpha (Attn.)	None	Custom	Acc.
Wang (2010)	Fractal Dim.	None	Custom	Acc., Engag.
Alchalabi (2018)	Attn.	Basic FB	Neuro.	Acc.
Belkacem (2015)	Eye+EEG	None	Custom	Dir. Acc.
Coyle (2011)	Motor Img.	Offline	BCI	Ctrl. Acc.
Ahn (2014)	Review	Adaptive	Multi	–
Bos (2010)	Mixed	FB Loop	BCI	Engag.
Nijholt (2009)	Conceptual	–	Vision	–
Malete (2019)	SSVEP	None	3D	Dir. Acc.
Bonnet (2013)	Motor Img.	Coop. FB	Multi	Consist.
Vourvopoulos (2017)	Motor Img.	NeuroFB	Rehab	Immers.
Prapas (2023)	Attn. (Fuzzy)	Thresh.	Puzzle	Attn. Score
Sterk (2022)	Motor Img.	Modular Sys	Unity	Acc.
Keutayeva (2025)	SSVEP	Review	Multi	–
Ma (2022)	NeuroFB	ADHD Pers.	Custom	WM, Acc.
Sawangjai (2019)	Review	–	Multi	Setup Usab.
Pantförder (2022)	Review	Acc. Design	Games	Persp., Immers.
Simar (2020)	Motor Img.	Pipeline Eval	FPS	Classif. Acc.
Glavaš (2022)	EEG+Emotion	Realtime Mon.	Gaming	Workload, Valence
Krigolson (2021)	EEG+ERP	Mobile Track	Multi	EEG Quality
Pinto (2021)	NeuroFB	Indiv. Baseline	Custom	WM, Persp.
Xie (2025)	ERP	Real-World Exp.	Study	Neural Patterns
Nouri (2025)	EEG+HRV	Immersive Eval	Custom	Emot., Immers.
Palumbo (2021)	Motor Img.	Not Specified	Maze	EEG Corr., Speed
Saichoo (2022)	SSVEP	FB Loop	Custom	Acc., FP
Tariq (2018)	Motor Img.	SVM Model	Maze	Classif. Acc.
An (2024)	ERP+SSVEP	Threshold	VR Maze	ERP, Latency
Pfurtscheller (2010)	ERD+SSVEP	Brain Switch	Orthosis	Ctrl. Acc., FP

Abbreviations used:

Attn.	Attention
FB	Feedback
Neuro.	Neurofeedback
Dir. Acc.	Directional Accuracy
Ctrl. Acc.	Control Accuracy
Engag.	Engagement
Img.	Imagery
Thresh.	Threshold
Acc.	Accuracy
Consist.	Consistency
Immers.	Immersion
Coop. FB	Cooperative Feedback
NeuroFB	Neurofeedback
WM	Working Memory
ERP	Event-Related Potential
HRV	Heart Rate Variability
Persp.	User Perspective
Mon.	Monitoring
Eval.	Evaluation
Corr.	Correlation

3 Methods

3.1 System Overview

We developed a real-time EEG-controlled game prototype by integrating the open-source racing game *Tux Racer* with brain signal input captured via the Muse S headband (4-channel EEG, sampled at 256 Hz). The system translates directional motor imagery into in-game controls (left, right, and idle). Our pipeline consists of the following components:

1. **Signal Acquisition:** Real-time EEG signals are captured using the Muse SDK and streamed to a Python-based interface.
2. **Preprocessing:** Raw EEG data is filtered using a 1–50 Hz bandpass and a 60 Hz notch filter to remove common artifacts.
3. **Feature Extraction:** Power spectral density (PSD) features are extracted from frontal and temporal channels, with a focus on alpha and beta frequency bands.
4. **Threshold Calibration:** A 90-second pre-game calibration session collects baseline mental state data for each participant. Thresholds for left, right, and idle commands are computed using mean and standard deviation of task-specific PSD activity, followed by cross-subject normalization.
5. **Decision and Feedback Module:** Incoming signals are matched against calibrated thresholds in real time. Detected intent triggers in-game movement. A feedback loop monitors recent predictions and adjusts the visual cue timing and reaction window to maintain engagement and challenge.

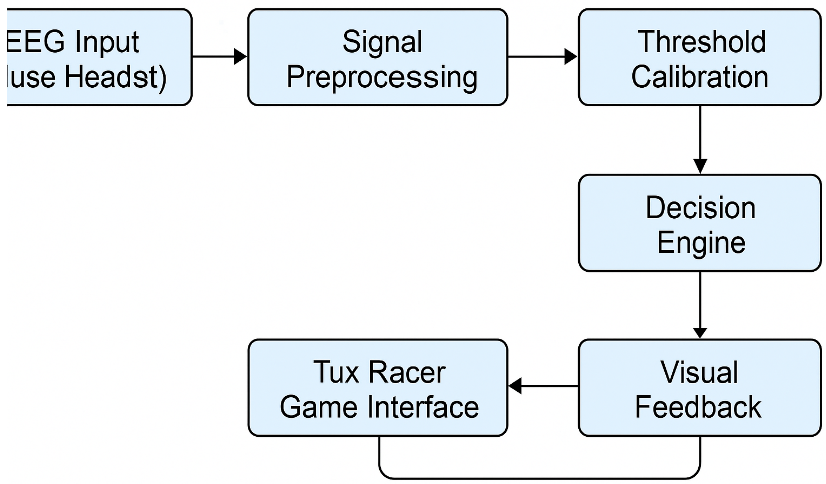

Fig. 1. System architecture diagram for EEG-based game control. EEG signals from the Muse headset are processed and translated into control signals for the Tux Racer game. Real-time visual feedback reinforces the user's intent through in-game movement.

Although this prototype uses the Muse S headset, the system architecture is modular and can be adapted for other EEG hardware platforms that support real-time data access.

3.2 Personalization Strategy

Our system emphasizes personalization through offline threshold calibration and dynamic feedback adaptation. Each participant's unique EEG patterns—captured during the pre-game calibration—are used to compute individualized thresholds that account for signal variability and mental fatigue. This avoids the limitations of one-size-fits-all models and enables intuitive control without requiring model retraining during gameplay.

3.3 Participant Recruitment and Demographics

Fifteen undergraduate students (8 male, 7 female), aged 19–21, from our Computer Science department participated in the study. All were right-handed or ambidextrous, though handedness was not formally recorded. None had prior experience with EEG systems or the Tux Racer game. Written informed consent was obtained from all participants.

The study was reviewed and approved by our university's Institutional Review Board (IRB). Ethical procedures included anonymized data collection, voluntary participation, and compliance with institutional data privacy guidelines.

3.4 Experimental Protocol

Participants were seated in a quiet room and fitted with the Muse S headband. Each session began with a 90-second pre-game calibration to generate individualized thresholds. Participants then completed three rounds of gameplay, each lasting 3–4 minutes, with rest breaks between rounds to mitigate fatigue.

During each round, directional cues (left, right, or idle) were presented at regular intervals. EEG responses were classified in real time, and corresponding control commands were executed in the game. Participants were encouraged to provide verbal feedback on system responsiveness and engagement.

3.5 Data Handling and Privacy

All EEG data were anonymized using randomly assigned participant IDs (e.g., Subject 1–15). No personal identifiers were recorded. After data collection, files were encrypted and stored on a secure, access-controlled institutional cloud platform. All data handling complied with university policy and IRB-approved ethical standards.

Fig. 2. Participant playing EEG-controlled Tux Racer during real-time trials.

4 Results

4.1 Directional Classification Accuracy

We evaluated the system's ability to decode directional intent—left, right, and idle—using real-time EEG signals. Accuracy was measured per participant across three post-calibration gameplay sessions. Table 2 summarizes average classification accuracy per direction for all participants.

Table 2. Average Classification Accuracy per Direction

Participant	Left (%)	Right (%)	Idle (%)
P1	65	72	85
P2	58	63	80
P3	70	73	82
P4	71	64	83
P5	67	68	87
P6	66	71	85
P7	75	73	86
P8	72	76	84
P9	63	71	80
P10	74	70	87
P11	69	72	83
P12	70	67	80
P13	68	72	81
P14	72	69	82
P15	70	68	87

Most participants achieved reasonable directional control accuracy, with idle states being the easiest to detect. One participant (P4) consistently triggered left turns regardless of intent, likely due to a poorly tuned threshold or alpha-band signal noise. These cases underscore the importance of robust and personalized calibration.

4.2 Usability and Engagement Feedback

Participants rated their experience across several dimensions using a 5-point Likert scale (5 = strongly agree). The results suggest generally high enjoyment, moderate control perception, and low to moderate fatigue. Table 3 summarizes average ratings.

Table 3. Participant Feedback Summary (1–5 Likert Scale)

Metric	Avg. Score	Min	Max
Enjoyment	4.1	3	5
Sense of Control	3.6	2	5
Mental Fatigue	2.8	1	4
Responsiveness	3.3	2	5
Calibration Difficulty	2.4	1	4

Verbal feedback emphasized novelty and engagement, with some participants noting mild frustration when feedback lagged or when sustained concentration was required for multiple rounds.

4.3 Effect of Personalization

To evaluate the impact of threshold personalization, we compared directional accuracy from the initial calibration phase (pre-personalization baseline) to post-calibration gameplay. Ten of fifteen participants showed noticeable improvement in control accuracy after personalization, with average gains between 8–12 percentage points.

We conducted a paired two-tailed t-test comparing mean directional accuracy across participants before and after personalization. The results were statistically significant ($t(14) = 3.21$, $p = 0.0065$), confirming that offline threshold calibration improved decoding performance.

4.4 Error Patterns and Challenges

Some participants encountered misclassification errors when attempting to switch mental states quickly or inconsistently. In particular, ambiguous EEG patterns during direction alternation led to incorrect predictions in real time. These findings suggest that future versions may benefit from real-time adaptive classifiers, additional sensing modalities, or more explicit cueing mechanisms to stabilize mental intent during transitions.

5 Discussion

This study demonstrates the feasibility of using a consumer-grade EEG headset for real-time game control through personalized threshold calibration. Even without online retraining or deep learning models, our system reliably translated motor imagery signals into gameplay actions using individualized thresholds and a lightweight decision engine.

5.1 Interpretation of Findings

Personalized pre-game calibration significantly improved control accuracy for most participants, highlighting the value of subject-specific tuning in non-clinical BCI settings. The use of Tux Racer—an open-source, mainstream game—combined with low-cost EEG hardware represents a novel, accessible approach for EEG-based game interaction.

5.2 Limitations

Our sample was limited to 15 undergraduate students from a single department, and the study used only one EEG device. The absence of a keyboard-based control condition and online adaptation also restricts long-term generalizability.

5.3 Future Directions

Future work will expand participant diversity, explore online threshold adjustment, and evaluate multimodal input integration (e.g., eye tracking, heart rate). We also aim to investigate applications in classroom and rehabilitation settings, where personalized EEG control may support cognitive training, emotional regulation, and inclusive gameplay.

6 Conclusion

We presented a real-time EEG-controlled version of Tux Racer that integrates personalized threshold calibration and feedback using a low-cost, consumer-grade EEG headset. The system enabled participants to navigate a mainstream game environment using non-invasive brain signals, without requiring complex classifiers or retraining. Our findings support the potential of accessible brain-computer interfaces for a wide range of interactive applications and provide a foundation for future work in personalized EEG-based control.

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