From Theory to Play: A Review of EEG-Controlled Directional Games and Evaluation of Custom-Developed BCI Games

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Abstract

Electroencephalography (EEG)-controlled games represent an emerging frontier in brain-computer interfaces (BCIs), offering hands-free interaction through neural signal decoding. This review paper systematically examines EEG-based directional control in gaming, focusing on motor imagery (MI) classification techniques and game design considerations. Through a PRISMA-guided literature review, we analyze 37 studies, identifying Linear Discriminant Analysis (LDA) as the dominant classification method while highlighting gaps in reproducibility and dataset diversity. We further evaluate three custom-developed EEG-controlled games—a rhythm game, a hide-and-seek game, and a snake game—assessing their usability and suitability for EEG data collection. Our findings reveal that simplified game mechanics with engaging gameplay are suitable for EEG data collection purposes. The paper also critiques the limitations of existing platforms like TuxRacer for BCI research and proposes best practices for future EEG gaming systems, emphasizing open datasets and adaptive modeling. By bridging game development and BCI research, this work lays a foundation for scalable, user-friendly EEG-controlled gaming ecosystems.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; • **Computing methodologies → Machine learning**.

Keywords

EEG Motor Imagery, EEG-controlled games, EEG directional control, EEG data collection, EEG signal classification, machine learning, deep learning

ACM Reference Format:
Wensi Xie, Jingwen Dou, Yiran Wang and Xiaodong Qu. 2025. From Theory to Play: A Review of EEG-Controlled Directional Games and Evaluation of Custom-Developed BCI Games. In *Proceedings of KDD Undergraduate Consortium (KDD-UC '25).* ACM, New York, NY, USA, 8 pages. https://doi.org/XXXXXXX.XXXXXXX

KDD-UC '25, Toronto, Canada

ACM ISBN 978-x-xxxx-xxxx-x/YYYY/MM
https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

Electroencephalography (EEG)-controlled games offer a novel paradigm in human-computer interaction, enabling hands-free control of digital environments by interpreting neural signals. As a non-invasive, low-cost input modality, EEG has the potential to support accessibility, gaming, and cognitive science. The intersection of brain-computer interfaces (BCI) and interactive systems has generated increasing interest. However, real-time EEG signal decoding remains technically challenging due to noise, individual variability, and the complexity of brain signal patterns.

Recent advances in machine learning have improved motor imagery (MI) signal classification [35], yet most EEG-controlled game systems remain constrained by limited-scale datasets, fragmented modeling methods, and an absence of reproducible, open-source pipelines. Moreover, few existing works incorporate real-time feedback or a user-participatory setup, further limiting their generalization and practical deployment.

To address these limitations, this paper presents a hybrid research project with three goals: (1) conduct a literature review of EEG-controlled directional games and associated signal classification techniques, (2) provide best practices to assist new researchers in familiarizing themselves with EEG-controlled games and their associated evaluation methodologies, and (3) conduct a comprehensive review of the open-source TUX Racer game, alongside the three games we have developed for EEG data collection. This approach lays the foundation for an open data ecosystem where everyday users can help researchers better understand how the human mind can control direction in games and beyond.

1.1 Research Questions

We structure our investigation around the following key questions:

- What are the most commonly used techniques for EEG signal classification in directional game control?
- How to design games to assist in EEG data collection and how to evaluate their effectiveness?

2 Related Work

EEG-controlled games, particularly those using directional control, sit at the intersection of brain-computer interfaces (BCIs), real-time signal processing, and human-computer interaction. While much of the EEG literature focuses on clinical applications and artifact removal, recent work has turned toward decoding user intent for interactive systems such as games, virtual environments, and assistive technologies.

2.1 EEG Signal Classification and Gaming

Motor imagery (MI)-based control is a common technique in EEG gaming, involving the mental rehearsal of movement to modulate neural activity. Deep learning models—especially Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid CNN-LSTM architectures—have been widely used to improve MI classification accuracy [2, 3, 10, 34]. Transformer-based architectures and attention-based CNNs have also shown promise in modeling long-range temporal dependencies and learning salient features [1, 8, 11, 14, 19, 22, 26, 28, 30, 31, 33, 37, 39, 43, 44, 46].

Yi and Qu [44] introduced a dual attention-CNN model capable of interpreting both global and local EEG signal changes. Yang et al. [43] adapted vision transformers to EEG, achieving strong results across varied BCI tasks. Xiang et al. [41] demonstrated that combining coarse- and fine-grained EEG training data improves robustness in gaze decoding, a principle we explore through hybrid gameplay training.

Key et al. [20] further advanced transformer-based EEG modeling, combining depthwise-separable CNNs with clustering-augmented preprocessing to reduce root mean square error on EEGEyeNet. These architecture-level insights directly inform our game-control modeling pipeline.

Despite such advancements, real-time decoding remains difficult due to variability across users and environments [12]. Our pipeline addresses this with architecture comparison and user-friendly data collection. Other recent work explores multidirectional MI decoding for real-time control scenarios. Amini and Shalchyan [4] apply motion-onset VEP to control virtual agents; Jeong et al. [17] demonstrate EEG-based robot control, while Cho et al. [9] focus on decoding natural grasp via EEG.

Abbreviation	Definition
BCI	Brain-Computer Interfaces
BiGRU-Attention	Bidirectional Gated Recurrent Units - Attention
CNN	Convolutional Neural Network
EEG	Electroencephalography
EGQ	EEG Game Questionnaire
FNNs	Functional Neural Networks
GAN	Generative Adversarial Network
LDA	Linear Discriminant Analysis
LSTM	Long Short-Term Memory
MI	Motor Imagery
MLP	Multi-Layer Perceptron
NBPW	Naive Bayesian Parzen Window classifier
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RL	Reinforcement Learning
RLDA	Recurrent LDA
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
SWNN	Small World Neural Network classifier
WPNN	Wavelet Packet Neural Network

Table 1: Abbreviation Table

2.2 Participatory and Open EEG Research

Open-source EEG pipelines have grown in popularity. Gil et al. introduced DISCOVER-EEG for automated preprocessing in clinical research [13], while Qu et al. [32] demonstrated EEG's utility in undergraduate research. Recent work by Williams et al. [40] explores crowdsourced EEG collection using EmotivPRO Builder, involving hundreds of participants in online resting-state experiments. We build on this participatory framework by enabling healthy users to contribute gameplay EEG data, supporting reproducibility and engagement in BCI studies.

2.3 Game Review Questionnaires

Two questionnaires are widely used in EEG studies to evaluate the usability and player engagement of EEG games: the System Usability Scale (SUS), a widely used 10-item questionnaire that provides a reliable measure of perceived usability, and the Game Experience Questionnaire (GEQ), a standardized tool designed to assess player experience across multiple dimensions, including immersion, flow, and enjoyment.

In this study, to specifically investigate the plausibility and effectiveness of EEG-controlled games, we developed a questionnaire called "EEG Game Questionnaire" (EGQ), which can be found in the Appendix section. This questionnaire comprises three targeted questions designed to assess the effectiveness of the game design for EEG data collection.

2.4 Limitations of Existing Game-Based EEG Experiments

Existing games used in EEG studies were not designed specifically for EEG input devices; thus, the use of these games could compromise data quality. Features such as camera smoothing or sudden movement changes may induce motion sickness [21] and continuous fragmentation of intent and feedback tends to lead to fatigue [24]. Poor audio design could also cause some negative impact on participants [25]. Additionally, these games often lack reliable performance metrics tied to user intent, hindering neural control evaluation.

2.5 EEG Game Review

This paper aims to assess the performance and usability of EEG-based gaming through a review of TUX Racer, an open-source racing game, as well as three games that we specifically designed and developed for experimental evaluation.

TuxRacer (Figure 4) is a 3D winter racing game where players control Tux the penguin, navigating snow-covered slopes, and is commonly used in BCI research for testing EEG-based input systems. Hide and Seek (Figure 2) involves the player remaining centered while catching a child character that briefly appears on either side, requiring quick directional movement. Rhythm Game (Figure 1) features falling notes aligned with the music beat, where players score by providing left or right input as notes reach the detection zone. Fruit-Lover Snake Game (Figure 3) offers a casual experience where players control a snake that grows by consuming fruit while avoiding self-collisions.

3 Methods

This section outlines our dual methodology: (1) a systematic literature review of EEG-controlled directional games using the PRISMA framework, and (2) an evaluative framework for analyzing and reviewing the three games developed in this study.

3.1 Systematic Literature Review (PRISMA)

We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to identify relevant studies on EEG-based game control and motor imagery (MI) classification. We focused specifically on papers applying machine learning to directional EEG control, particularly in real-time or interactive applications.

Databases: Google Scholar, IEEE Xplore, ACM Digital Library, arXiv **Keywords:** *(EEG AND (Motor Imagery OR Real-Time) AND (Directional Control OR BCI Gaming OR Signal Preprocessing OR Feature Extraction) AND (Deep Learning OR Classification))* **Timeframe:** January 2015 – March 2025

Inclusion criteria:

- Studies focused on EEG-controlled directional games or MI-based BCI systems.
- Methods involving deep learning, signal preprocessing, or adaptive modeling.
- Published in peer-reviewed venues or widely referenced preprints.

Exclusion criteria:

- Studies focused only on clinical EEG use (e.g., seizure detection).
- Non-interactive applications with no real-time feedback loop.
- Theoretical works without empirical results.

We coded each eligible paper using a structured extraction form, tagging information such as feature extraction algorithm, classification algorithm, and accuracy. Each paper was independently reviewed by two researchers for consistency.

Following screening, 37 studies met all inclusion criteria, and 21 of them were used in statistics (Figure 5). Our goal was to identify trends in model selection, reproducibility practices, and real-time system design for EEG-based games.

Figure 5 illustrates the PRISMA-based search and selection process.

3.2 Game Design

Based on the shortcomings of existing games and considering the high latency and relatively low accuracy issues inherent to motor

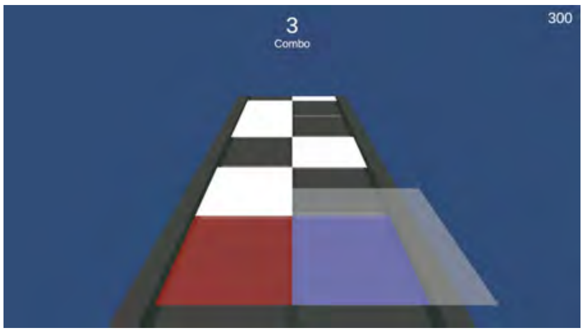

Figure 1: A rhythm game designed to evaluate EEG-based directional control.

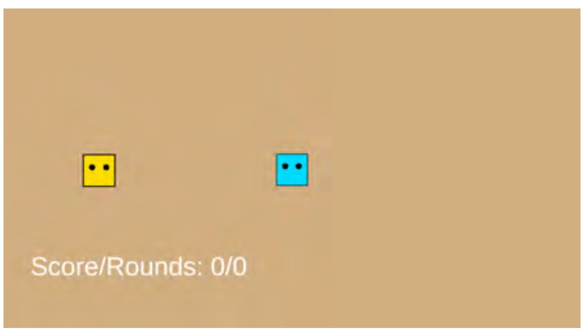

Figure 2: Game prototype we designed used to assess real-time directional EEG control performance.

Figure 3: Fruit-Lover Snake, a game we developed to cater to more casual players

Figure 4: TuxRacer game

imagery (MI) BCI interfaces, we propose the following fundamental principles for game design in MI-BCI research:

(1) **Avoid interference from complex in-game environments** that could disrupt player control.
(2) **Ensure intuitive audiovisual feedback** that directly reflects the player's inputs.
(3) **Minimize the learning curve** to prevent fatigue accumulation during the learning process.
(4) **Reduce reliance on physiological factors** such as reaction speed and visual sensitivity.
(5) **Simplify game mechanics and lower task complexity**, favoring designs that align with natural human intuition.

Based on principles, we developed three games, and each game was evaluated using the EEG Game pipeline through both qualitative and quantitative methods.

For quantitative analysis, we used two metrics: the game score, representing task completion, and the controllability score, measuring how effectively the player controlled the avatar. As we did not modify Tux Racer's source code, controllability could not be calculated for that game. Each game uses a different scoring system (Table 3): the snake game counts the number of fruits collected in 60 seconds; hide-and-seek counts correct directional inputs over total rounds; the rhythm game counts correct key presses within one minute; and Tux Racer counts the number of fish collected before finishing.

Controllability scores further reflect control quality: in the snake game, this is based on how efficiently players collect food, factoring in speed, precision, and directness; in hide-and-seek, it measures how accurately and steadily players move toward the child; and in the rhythm game, it captures response speed and timing accuracy, penalizing incorrect or delayed inputs.

For the qualitative assessment, we administered three questionnaires: SUS, GEQ, and the EGQ, the latter developed by the authors. These instruments provide a structured framework for assessing usability and user engagement. All evaluation metrics were completed by the authors to offer a preliminary assessment of the games' design and functionality.

3.3 Evaluation Framework

For both literature and system evaluation, we used the following four criteria:

- **Classification Method**: reviewed classification method or classification methods used.
- **Accuracy**: Correct classification of directional EEG intent.
- **Dataset**: Dataset used, along with the number of subjects contributing to it.
- **Reproducibility**: Ease of deployment and external validation

This methodology supports both a rigorous review of existing work and a reproducible path toward community-scale EEG gaming research.

4 Results

Our results synthesize findings from the systematic literature review and evaluate the usability and design of our EEG-controlled game. We summarize modeling techniques, accuracy, performance metrics, and data acquisition methods from the literature, then present the results from evaluating and reviewing our games. All the data and code will be uploaded to GitHub.

4.1 Findings from the Literature Review

Our systematic review identified and analyzed 37 peer-reviewed papers focusing on EEG-controlled directional games and motor imagery-based classification models. 21 of the review papers were used in statistics. As presented in Table 2, the methodological distribution reveals that Linear Discriminant Analysis (LDA) constitutes the predominant classification technique, employed in 52.38% of the examined studies, likely due to its computational efficiency and proven effectiveness in real-time BCI applications. Notably, while the majority of studies adopted conventional machine learning approaches, a subset implemented custom or hybrid methodologies, suggesting emerging trends toward more sophisticated classification pipelines. These findings underscore LDA's continued dominance in motor imagery classification while highlighting opportunities for innovation through alternative algorithmic approaches.

The most common evaluation metrics included:

- Classification accuracy (used in 70% of studies)
- Gameplay metrics (score, distance-to-target [6], avatar deviation)
- User feedback (surveys or engagement scores) (used in only 10% of studies)

Our review also found that very few studies provided reproducibility assets (e.g., code or datasets), highlighting the need for open pipelines like ours.

4.1.1 Best Practices and Recommended Pipelines. In addition to summarizing modeling trends, we identified a few key studies that exemplify best practices in EEG-based game pipeline design. These works offer well-documented methods, reproducible evaluation

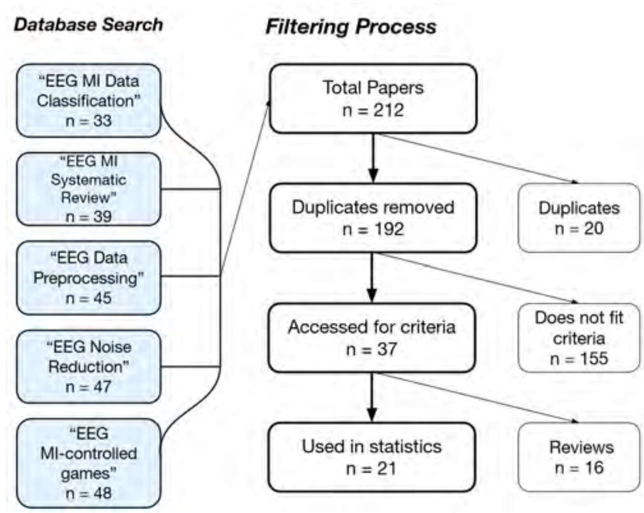

Figure 5: PRISMA Flowchart for Literature Review

frameworks, and a balanced integration of both quantitative and qualitative performance metrics. For example, [5, 6, 42] provide detailed accounts of real-time EEG game systems with rigorous accuracy evaluations, while [36, 38] incorporate user experience measures such as engagement, perceived control, and usability.

We recommend these papers as valuable entry points for researchers new to real-time EEG gaming. They demonstrate end-to-end workflows from signal acquisition to control mapping, and highlight critical design considerations such as latency handling, visual feedback timing, and experimental repeatability.

4.2 Game Evaluation

Table 3 presents the usability and user experience scores for the three games evaluated in this study. The SUS results indicate that Snake Game and Hide and Seek score above the established baseline of 68, demonstrating above-average usability. Analysis of the GEQ scores reveals two notable trends. First, the custom-designed games showed limited performance in generating immersion and presenting tension to players, but they achieved relatively high scores in key areas, including competence, flow, positive affect, and negative affect (reverse-coded). The EGQ scores also demonstrated how the EEG Game can contribute to data collection. In contrast, the TUX Racer scored relatively high on negative affect, indicating that there are some design flaws.

Table 4 shows the game score and controllability score of the four games. The controllability scores for each game are below 51%, indicating that players are unable to achieve the same level of avatar control using EEG as they can with a keyboard. Scores are calculated as follows: in Snake Game, based on the food collected in one minute; in Hide and Seek, as the ratio of children caught to total children appeared; in Rhythm Game, by the number of notes hit in one minute; and in TUX Racer, by the fish collected in one minute.

Modeling Technique	Paper Count	Accuracy
LDA	11	69%
SWNN	1	NM
MLP	1	59%
LSTM, CNN	1	72%
NBPW	1	74%
SVM	1	76%
RLDA	1	90%
RL	1	72%
BiGRU-Attention	1	90%
WPNN	1	89%
FNNs	1	58%

Table 2: Summary of techniques used in reviewed EEG directional control papers. NM stands for not mentioned. The accuracy of LDA is the average accuracy between the eleven papers.

5 Discussion

5.1 Insights from the Literature Review

Our systematic review of 37 papers on EEG-controlled directional games reveals two key trends in the field. First, Linear Discriminant Analysis (LDA) is used as the most prevalent classifier, alongside an emerging interest in custom and hybrid algorithmic approaches. However, a critical limitation persists: the majority of studies fail to provide open-source implementations or reproducible evaluation pipelines, which hinders scalability and generalizability. Furthermore, we observed substantial variability in reported classification accuracy across studies, likely attributable to the absence of standardized evaluation protocols for EEG-controlled gaming systems. These findings underscore the need for more transparent, community-driven research practices to advance the field.

The number of participants in these studies remains limited (typically 2-10 participants), and there is a lack of in-depth exploration or systematic analysis of the gaming experience; Instead, the

Game	Snake Game	Hide and Seek	Rhythm Game	TUX Racer
SUS	75	92.5	65	62.5
GEQ-Competence	1.8	2.4	2.2	1
GEQ-Immersion	1.16	0.6667	1.8	0.7
GEQ-Flow	o.8	2.6	2.2	1.6
GEQ-Tension	0.3333	1.3333	1.3333	1.7
GEQ-Challenge	0.6	1.2	2.4	1.4
GEQ-Negative Affect	0.75	0.75	0.75	1.5
GEQ-Positive Affect	2.6	2.4	2	2.2
EGQ-1	4	3	4	3
EGQ-2	3	1	2	3
EGQ-3	3	4	5	5
EGQ-4	3	3	2	4
EGQ-5	2	3	2	2

Table 3: Questionnaire results for each of our games

Game	Snake Game	Hide and Seek	Rhythm Game	TUX Racer
Score	6	90.67%	3900/8000	3.667
Controllability Score	0.315	0.51	0.374	N/A

Table 4: Quantitative results after playing the four games

performance of EEG as a controller is often assessed using simple quantitative metrics [6][26].

5.2 Limitations of TuxRacer for Motor Imagery BCI Research

While TuxRacer is frequently utilized in EEG research due to its open-source nature and visually engaging environment, our evaluation highlights several significant limitations when applied to motor imagery-based brain-computer interface (BCI) experiments.

Firstly, the game's acceleration-driven control system lacks an intuitive and consistent directional mapping, complicating the accurate assessment of user input precision. Scoring, which hinges on coin collection, is more strongly influenced by the player's route familiarity than by the accuracy of control. Moreover, the game's delayed follow-camera introduces perceptual lag and spatial disorientation, leading to a misalignment between the user's input and the visual feedback. This disconnect may introduce noise into EEG data, undermining the reliability of the experiment.

Additionally, the continuous control demands and absence of angular constraints present challenges in light of the high latency and limited precision inherent in EEG-based inputs. These design mismatches conflict with foundational principles of BCI experimentation, which emphasize reducing cognitive load, minimizing confounding variables, and ensuring a clear and natural mapping between user input and system response.

5.3 Analysis of Our Games

5.3.1 Rhythm Game. In the context of EEG-based research, rhythm games (music games) offer several advantages, both in terms of data collection and user engagement. Notably, they transform music—traditionally considered a confounding factor for EEG signals—into an essential and structured cue for interaction. Rhythm games inherently resolve this issue by eliminating the dependence of core interactions on contextual synchronization. Moreover, the use of smooth, steady-tempo music provides a more stable cognitive environment, potentially facilitating the emergence and classification of motor imagery (MI) intentions.

5.3.2 Snake Game. In our implementation of *Snake*, we modernized the visual design to enhance immersion and playability while simultaneously reducing cognitive load. When participants are treated as players, data collection becomes not only more efficient but also more sustainable over longer experimental sessions, as gameplay can mitigate fatigue. To support this, we adapted the original *Snake* game to increase its tolerance for control inaccuracies, thereby reducing user frustration.

5.3.3 Hide and Seek. Encapsulating left and right motor imagery (MI) commands within the framework of a hide-and-seek game further emphasizes the importance of playful design in increasing participant engagement. By presenting the task through the lens of a childlike, innocent form of fun, the game becomes more approachable and emotionally resonant. Similar to our adaptation of the classic Snake game, this design choice broadens the appeal of the system, making a wider range of participants more willing to interact with the BCI task as a game rather than as a rigid experimental protocol.

5.4 Recommendations for Future Work

Based on our findings, we recommend the following directions for future EEG gaming and BCI research in data science:

(1) **Benchmark Open Datasets**: Encourage standardization of directional EEG game datasets with shared protocols, model evaluations, and reproducibility scores.
(2) **Diverse User Testing**: With our custom-developed games and questionnaires, we will expand participant pools to include diverse brain signal profiles across age, gender, and gaming experience.
(3) **EEG Data Collection Using Games**: We will release our games on GitHub to facilitate broader adoption by researchers. By providing accessible tools for EEG data collection, we aim to lower barriers to participation and encourage contributions to a communal dataset.
(4) **Systematic Reviews of Real-Time BCI**: Current reviews often focus on static, offline motor imagery decoding. We recommend more systematic surveys dedicated to *real-time* BCI systems, especially those involving closed-loop feedback, online model adaptation, and longitudinal user performance tracking.
(5) **Game-Based BCI Evaluation Tools**: Our games aim to evolve into reliable tools for collecting and evaluating real-time EEG signals during gameplay. Future iterations could support the embedding of structured command recording and training into the game itself.

Our contribution provides a replicable baseline for future BCI applications that benefit from participatory signal collection and real-time ML-based adaptation.

6 Conclusion

This paper presents a dual contribution to the field of EEG-controlled gaming: a review of directional EEG control classification methods and a review of game prototypes suitable for EEG data collection. Our review underscores the preeminence of Linear Discriminant Analysis (LDA) architecture in real-time EEG classification for gaming applications, while also identifying two notable shortcomings in the existing literature: the absence of reproducible experimental pipelines and the limited availability of large, diverse datasets.

Most importantly, we introduce multiple games that invite healthy participants to contribute gameplay EEG data, helping to bridge the gap between research and real-world deployment. This participatory approach can accelerate benchmarking, personalization, and broader inclusion in brain-computer interface research.

Future work will expand our dataset, refine adaptive learning methods, and scale community engagement to enable reproducible, human-centered BCI systems.

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Appendix

This questionnaire (Table 5), which specifically targets EEG-controlled games, will be integrated with GEQ and SUS to form a comprehensive instrument for post-gameplay feedback. In the upcoming year, we aim to administer this combined questionnaire to approximately 30–50 participants following their engagement with our EEG-based games, thereby facilitating a robust evaluation of user experience and system effectiveness.

Table 5: EEG Game Questionnaire (EGQ) that we designed specifically for EEG games. 1 indicates strongly disagree, and 5 indicates strongly agree

	Question	**1**	**2**	**3**	**4**	**5**
1	I think using an EEG controller makes the game more fun than a traditional controller.					
2	The EEG has high mental demands that I cannot make timely decisions in the game.					
3	I prefer playing this EEG game over participating in a traditional EEG data collection session.					
4	I felt mentally exhausted while playing this game using EEG control.					
5	I felt the EEG controller responded to my intention.					