A Systematic Review of Consumer-Grade EEG Applications in Directional Game Control via Motor Imagery

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Abstract. This systematic review examines the current state of consumer-grade EEG-controlled directional games, focusing on motor imagery (MI) techniques. We analyze peer-reviewed studies to identify prevalent signal processing methods, classification algorithms, performance metrics, and game design approaches. Our findings reveal that Common Spatial Patterns (CSP) and Linear Discriminant Analysis (LDA) remain dominant for feature extraction and classification, respectively, due to their computational efficiency in real-time applications. The Unity game engine emerges as the preferred development platform, and evaluation metrics show a strong bias toward quantitative measures. Key challenges include inherent system latency (1–3.5 seconds), limitation on game design, and a lack of standardized evaluation frameworks. The review highlights critical gaps in current research, particularly the need for enhanced entertainment value alongside technical optimization, and provides practical guidelines for developing EEG-controlled games. These insights aim to facilitate the transition from experimental systems to engaging, consumer-ready applications while establishing directions for future research in this evolving interdisciplinary field.

Keywords: EEG Motor Imagery · BCI Game · Performance Metric · Review

1 Introduction

1.1 Motivation and Scope

The rapid development of Brain-Computer Interface (BCI) technologies has enabled novel forms of human-computer interaction, expanding the possibilities for user engagement across areas such as gaming and neurorehabilitation. Among the various BCI paradigms, Electroencephalography (EEG)-based systems have gained significant attention due to their non-invasiveness, affordability, and increasing commercial accessibility.

One promising application of EEG-based BCI is the use of *motor imagery* (MI)—a mental process where users imagine specific physical movements without actual execution—to control interactive systems. In recent years, EEG-controlled games utilizing MI have emerged as an innovative application.

Despite the growing interest in EEG-controlled directional games, the research landscape remains fragmented. Techniques vary widely across studies, performance metrics lack standardization, and studies ignore user engagement. This review aims to systematically examine the use of EEG motor imagery with commercially available EEG headsets for directional game control. The paper consolidates current methodologies, evaluates performance metrics, and identifies key trends and challenges, ultimately offering insights and step-by-step guides for future development in this emerging field.

1.2 Research Questions

To guide the structure of this review, we propose the following research questions:

- **RQ1:** What are the most commonly used techniques for implementing EEG-based motor imagery control in directional games?
- **RQ2:** What performance metrics are typically used to evaluate the effectiveness of real-time EEG-based game control?
- **RQ3:** What are the current trends, limitations, and open challenges in the development of such systems using consumer-grade EEG devices?

2 Related Works

2.1 EEG game pipeline

This subsection provides an overview of the core components involved in developing EEG-based games, outlining the standard pipeline from EEG signal processing to gameplay integration.

Signal Pre-processing and Feature Extraction EEG recordings are often contaminated with noise and artifacts caused by environmental noise or physiological activities like electric current or eye blinks. To address this, commonly employed noise and artifact removal techniques include filtering, ICA and regression-based methods [28, 3]. Following artifact removal, feature extraction techniques such as CSP, FFT, and wavelet transforms are applied to distill temporal and spatial information from the cleaned EEG signals [28]. A detailed overview of feature extraction methods is provided in Sharma et al. [71].

Classification Linear Discriminant Analysis (LDA) remains one of the most widely used classification techniques in EEG-controlled games, primarily due to its computational efficiency [34]. CNN, LSTM, and ViTs have higher classification accuracy, but need the support of large training data and are more computationally intensive than LDA [23, 34, 35, 40, 53, 64–66, 70, 79, 89].

Game Design and Development Unity dominates as the primary development platform for EEG-controlled games, largely due to its flexibility, extensive documentation, and strong community support. In addition to Unity, some researchers utilize specific code libraries or frameworks to meet particular development needs or to accelerate the game development process [60].

Motor imagery-based BCI games generally fall into four main genres: action, puzzle, adventure, and simulation. Among these, action games are the most prevalent, accounting for approximately 50% of the studies [24].

Table 1. Abbreviations for the terms used in this paper

Abbreviation	**Full Term**	**Abbreviation**	**Full Term**
BCI	Brain-Computer Interface	BP	Band Power
CNN	Convolutional Neural Network	CSP	Common Spatial Patterns
EEG	Electroencephalography	ERD	Event Related Desynchronization
ERS	Event Related Synchronization	FFT	Fast Fourier Transform
FIR	Finite Impulse Response	FPR	False Positive Rate
GD	Gamer Dedication questionnaire	GEQ	Game Experience Questionnaire
ICA	Independent Component Analysis	LDA	Linear Discriminant Analysis
LSTM	Long Short-Term Memory	MI	Motor Imagery
NASA-TLX	NASA Task Load Index	NBPW	Naive Bayesian Parzen Window classifier
NM	Not Mentioned	RLDA	Regularized Linear Discriminant Analysis
SMR	Sensorimotor Rhythm	SNR	Signal-To-Noise Ratio
SSVEP	Steady-State Visual Evoked Potential	SUS	System Usability Scale
SVM	Support Vector Machine	SWNN	Small World Neural Network classifier
TBR	Theta/Beta Ratio	TPR	True Positive Rate
ViT	Vision Transformers	VMIQ2	Vividness of Movement Imagery Questionnaire-2

2.2 EEG Game Performance Metric

Evaluating the performance of EEG-controlled games requires more than classification accuracy alone; it also encompasses user experience, sense of control, and other usability-related factors.

Quantitative Approach Game score and classification accuracy is usually used to evaluate both user performance and the effectiveness of the classification algorithm. To further evaluate the user's level of control, some studies have proposed specific formulas to quantify how effectively participants interact with the game. Arpaia et al. introduced the CoinError (CE) metric, which measures player performance by calculating the average normalized distance between the avatar and each coin [13].

Qualitative Approach Questionnaires are used to qualitatively evaluate EEG-controlled game systems, focusing on aspects such as usability, user experience, cognitive workload, and overall satisfaction. These subjective measures complement quantitative performance metrics by capturing how users perceive and interact with the system. Among the most commonly used tools are GEQ, NASA-TLX, and SUS. GEQ is designed specifically to evaluate players' experiences during digital gameplay, whil NASA-TLX assesses the perceived workload experienced by users when interacting with a system. SUS assesss a system's overall usability by producing a single score.

3 Methods

We conducted a comprehensive literature review focusing on EEG-controlled games, particularly directional control games, guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. Major databases searched included Google Scholar, IEEE Xplore, and NYU Library.

3.1 Keywords

To ensure comprehensive coverage, we employed systematic search strategies using combinations of relevant keywords. The keywords were divided into three groups as in table 2. The terms within a group are connected with OR operators, and the groups are connected using AND operators.

3.2 Screening and Selection Criteria

The initial reviewed papers were added to Zotero, which is a reference manager. Duplicates were automatically detected and removed using Zotero. Then, a series of criteria were applied to exclude irrelevant papers. Papers were included only if they met all of the following Selection Criteria.

– **Format:** Written in English and published in peer-reviewed scientific journals or conferences.
– **Publication Time Frame:** We included papers from 2015 onwards to capture the most recent advancements.

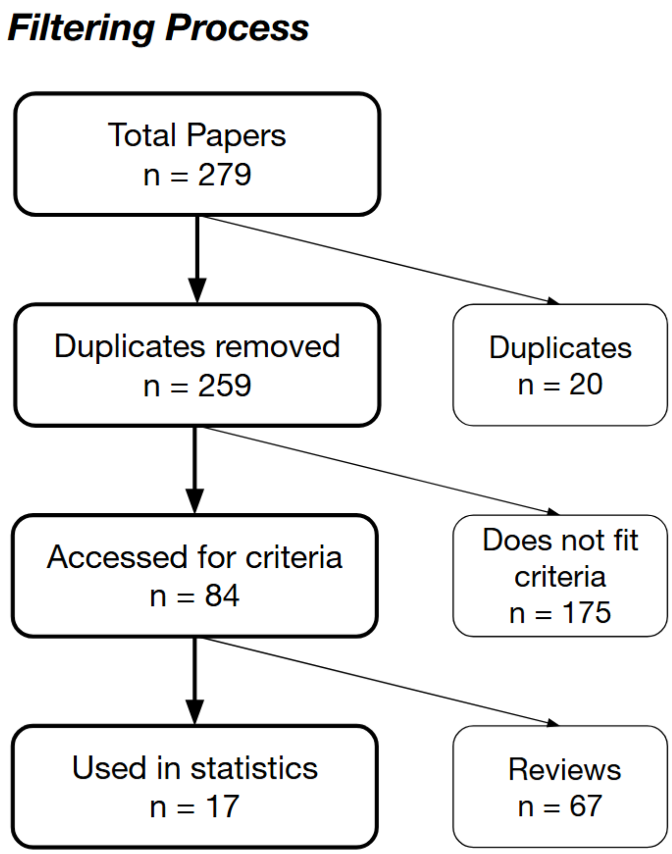

Fig. 1. Selection process for the papers

Table 2. Grouped keywords for structured literature search strategy.

Paradigm	**Game**	**Paper Type**
EEG Motor Imagery	Game	Review
Realtime EEG MI	Video Game	Experiment
Realtime EEG-controlled	Virtual Reality Game	Survey
EEG directional control	Game Performance Metric	Classification
	Game Performance Evaluation	

- **Directional Control Focus:** Papers must specifically address MI EEG-controlled directional games or techniques directly applicable to directional control.
- **Application Domain:** Preference was given to studies focusing on real-time interactive applications, particularly gaming, rather than purely clinical or rehabilitative contexts.
- **Technical Depth:** Papers must discuss EEG signal processing, motor imagery techniques, or the application of deep learning methods for control tasks.

3.3 Information Extraction

To systematically analyze the current state of EEG-controlled directional games using motor imagery and consumer-grade devices, we conducted a structured data extraction process from 17 selected peer-reviewed papers. The information extracted was designed to comprehensively address all three research questions. We focused on capturing a broad but consistent set of features from each study that could collectively inform our understanding of the techniques used, the performance metrics applied, and the overall challenges and trends in the field.

The following key information was extracted from each eligible paper:

1. **Signal Processing Techniques**: This includes methods used for EEG signal preprocessing and feature extraction.
2. **Classification Methods**: The algorithms used to classify the extracted features into directional commands.
3. **Classification Accuracy**: Reported performance in terms of classification accuracy for the directional control task.
4. **Mental Tasks**: The specific types of motor imagery tasks employed in the study, such as imagined left-hand or right-hand movements.
5. **Game Content**: A description of the game used in the study.
6. **Performance Metrics**: Both quantitative and qualitative metrics used to evaluate game performance and user experience.
7. **Average Game Score**: The average scores achieved by participants in the game. This provides a practical measure of system usability and player performance beyond classification accuracy.
8. **Latency**: The time window or sliding window size used for real-time classification.
9. **Game Engine**: The software framework or platform used to develop the EEG-controlled game. Understanding the development environment helps evaluate the system's scalability and integration potential.

All extracted information was recorded in a structured Microsoft Excel spreadsheet. The data were further synthesized into tables and visualized through figures. Tables were written in LaTeX format, while figures were generated using the Pyplot library.

4 Results

A total of 279 papers were found that are related to EEG motor imagery controlled game. 20 duplicate papers were removed, and 175 papers were exlucded because they did not fit the selection criteria. 84 papers were included in this review, and 17 of them were reviewed and used in statistics. The full table of collected data is included in the appendix section.

4.1 EEG Signal Processing Techniques

Table 3 summarizes key aspects of EEG signal processing in gaming pipelines, including pre-processing methods, feature extraction and classification techniques, mental tasks, and achieved accuracy. Figures 2 and 3 display the adoption frequency of different feature extraction and classification methods across studies. The results show that Common Spatial Patterns was the dominant feature extraction method (12/17 studies), while Linear Discriminant Analysis was the most prevalent classification technique (11/17 studies).

4.2 Game Performance Metrics and Game Score Analysis

Table 4 provides a comprehensive overview of game content, performance evaluation metrics (both quantitative and qualitative), and corresponding average game scores (expressed as percentages) across studies. The scoring methodology varies between studies, with some employing task-specific metrics like coins collected while others utilize classification accuracy. Figure 6 illustrates the distribution of studies employing quantitative versus qualitative assessment approaches.

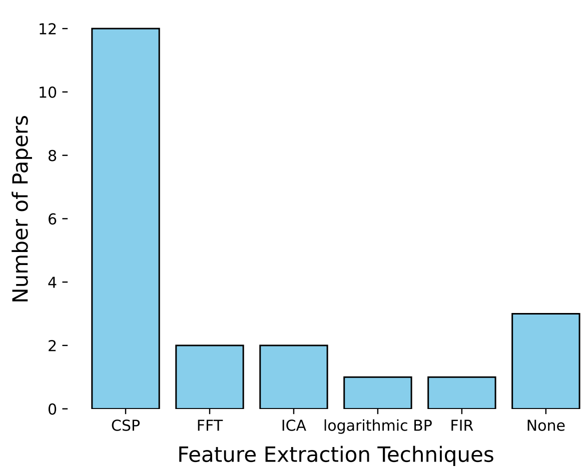

Fig. 2. Number of papers that used each feature extraction technique

Table 3. Summary of signal pre-processing methods, feature extraction methods, classification techniques, mental tasks, and reported accuracies in Reviewed Studies

Paper	Signal Pre-processing	Feature Extraction	Classifier	Mental Task	Accuracy
[12]	bandpass filter	CSP	LDA	left/right hand, and no MI	None
[88]	bandpass filter	CSP	LDA	left/right hand	70%
[39]	power frequency filtering, EOG extraction, and baseline correction of EEG	ICA, CSP	SWNN	left/right hand, feet, tongue, single/double blink	None
[62]	bandpass filter	None	LDA	left/right hand, blink	None
[13]	bandpass filter	CSP	LDA	left/right hand	None
[63]	bandpass filter	None	MLP	left/right hand, blink	None
[84]	None	CSP	LDA	left/right hand	63.19%
[33]	a self-designed spatial filter, bandpass filter	None	LDA	left/right hand	65%
[41]	None	CSP	LDA	left/right hand, both feet, tongue	70%
[50]	python and MNE library AND bandpass filter	FIR	LSTM and CNN	left/right hand, head movement	72% and 70%
[11]	Filter Bank (FB) composed by an array of bandpass filters	CSP	NBPW	left/right hand	74%
[75]	bandpass filter	FFT, CSP	LDA	left/right hand	58.3%
[76]	None	FFT, CSP	LDA	left/right hand	None
[20]	None	ICA	SVM	left/right hand	76%
[36]	bandpass filter	CSP	RLDA	left/right hand, feet, relax	90%
[86]	bandpass filter	CSP	LDA	left/right hand+SSVEP	87.01%
[45]	None	BP, CSP	LDA	left/right hand	None

Analysis reveals that quantitative performance metrics (e.g., coins collected, classification accuracy, CoinError) were employed in the majority of studies (16/17) to evaluate EEG game pipeline efficacy, whereas only 35.3% (6/17) incorporated both quantitative and qualitative measures. For qualitative assessment, while some studies developed custom questionnaires to assess user experience and system efficiency, most adopted established instruments including SUS, NASA-TLX, and GEQ.

Notably, two studies reported participant feedback indicating high mental demands coupled with low physical/temporal demands and frustration levels [13, 84]. Another investigation employed ERD/ERS and SMR analysis to quantify participant fatigue, demonstrating that demanding motor imagery tasks increasing fatigue levels subsequently impaired performance through diminished attention and engagement [76].

4.3 Additional Technical and Development Characteristics

Table 5 summarizes the mental tasks employed for EEG signal acquisition and the sliding window durations (latency) used for classification. Figure 3 illustrates the distribution of game engines adopted in EEG-controlled game development.

The analysis reveals that Unity was the predominant choice, utilized in 83.3% of the reviewed studies, while Unreal Engine and Qt Creator were employed in only 8.3% and 8.3% of studies, respectively. Notably, one study highlighted Unity's adoption despite the authors' lack of prior game development experience, citing its user-friendly development environment as a key factor [33].

Concerning mental tasks, all studies incorporated left- and right-hand motor imagery as primary control mechanisms. Some extended functionality by

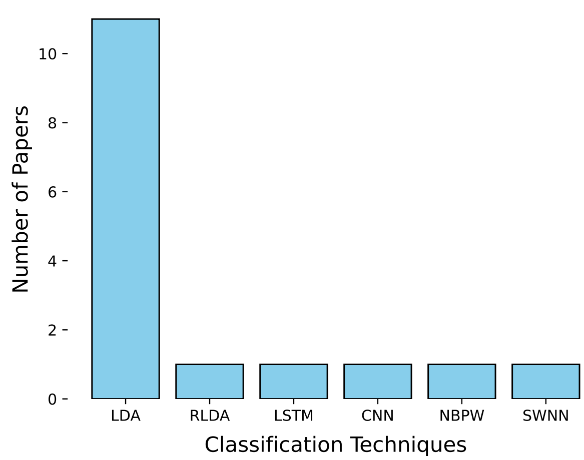

Fig. 3. Number of papers that used each classification technique

Table 4. Summary of the game content, performance metrics, and average game scores of the reviewed studies

Paper	Game	Quantitative Performance Metric	Qualitative Performance Metric	Average Game Score
[12]	Collecting coins in three lanes	Score, Coin-Error(CE)	Self designed questionnaires	32.24%
[88]	Keep a ball from falling off the platform	game score, SMR and TBR, a formula for sense of control	None	None
[39]	3D Tetris	Score, ERD and ERS	None	None
[62]	Collecting coins in three lanes	Score, Coin Clusters Collected, Accuracy	None	65.80%
[13]	Collecting coins in three lanes	CoinError (CE)	SUS, NASA-TLX	36.57%
[63]	Collecting coins in three lanes	Score, Coin Clusters Collected, Accuracy	None	59%
[84]	Rowing a boat to collect flags	Score	VMIQ2, GD, NASA TLX, GEQ, SUS	None
[33]	Collecting fruits on trees alongside a path	Accuracy	None	65%
[41]	Maze	Accuracy	None	70%
[50]	Super Mario game	Accuracy	None	72% and 70%
[11]	Sliding a ball toward a given target	Accuracy	Self designed questionnaire on a 7-point Likert scale	74%
[75]	using the cued hand to push a button	Accuracy	NASA TLX, a self-designed questionnaire	58.30%
[76]	Destroying Asteroids	Score, Accuracy, Bit Transfer Rate, ERD	self designed quetionnaire on a Likert scale	67.11%
[20]	Choosing from two objects to place on a trash bin	Accuracy	None	76%
[36]	A car racing game	Accuracy	None	90%
[86]	2D tetris	Accuracy, TPR, FPR	None	87.01%
[45]	Rotating shapes to solve puzzles	None	None	None

integrating additional commands (e.g., jumping or rotating), which required alternative imagined movements, such as foot movement, tongue movement, or blinking. While details on sliding window length were frequently unreported, studies that did specify this parameter employed durations ranging from 1 to 3.5 seconds.

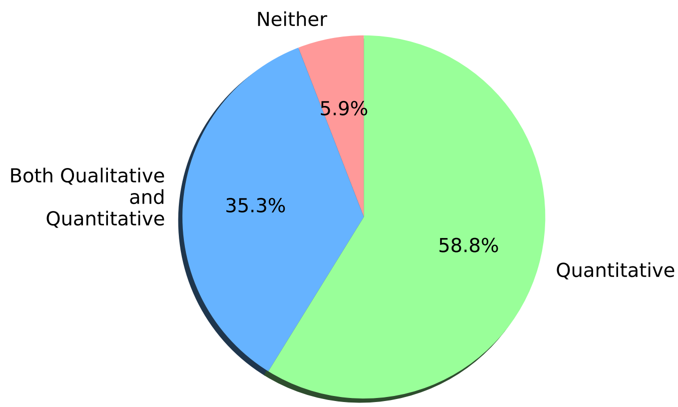

Fig. 4. Percent of papers that used quantitative and/or qualitative performance metric

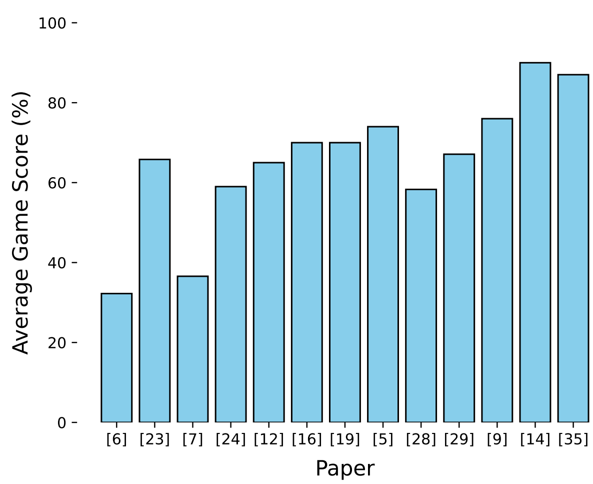

Fig. 5. Each paper's average game scores (in percentage)

5 Discussion

This subsection synthesizes key findings into a framework for constructing an EEG-controlled directional game system, while addressing current trends and challenges in EEG-game integration.

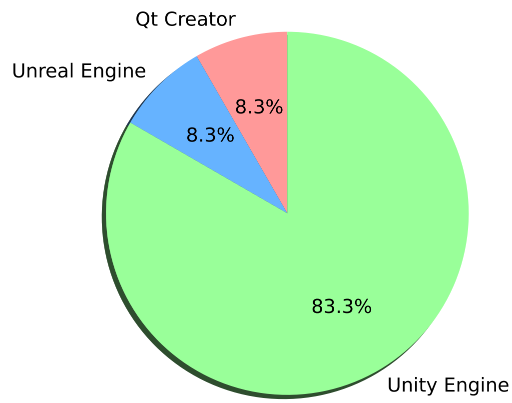

Fig. 6. Percent of studies that used each game engine

Table 5. Mental tasks used and the sliding window length for analyzing EEG signals.

Paper	Mental Task	Latency (seconds)	Paper	Mental Task	Latency (seconds)
[12]	left/right hand, and no MI	NM	[88]	left/right hand	NM
[39]	left/right hand, feet, tongue, single/double blink	1.43	[62]	left/right hand, blink	NM
[13]	left/right hand	NM	[63]	left/right hand, blink	3
[84]	left/right hand	NM	[33]	left/right hand	NM
[41]	left/right hand, both feet, tongue	NM	[50]	left/right hand, head movement	NM
[11]	left/right hand	2	[75]	left/right hand	3.5
[76]	left/right hand	Customizable	[20]	left/right hand	NM
[36]	left/right hand, feet, relax	1-2	[86]	left/right hand+SSVEP	2
[45]	left/right hand	1			

5.1 General Framework for Developing an EEG-Controlled Game System

EEG Signal Acquisition The majority of reviewed studies employed commercial EEG headsets with 4 to 20 electrodes. While higher-density configurations improve signal resolution, they prolonged setup times and increased computational demands, which may compromise real-time performance.

Signal Processing and Classification For researchers new to EEG, we recommend adopting Common Spatial Patterns (CSP) for feature extraction and Linear Discriminant Analysis (LDA) for classification. These methods dominate the literature due to their computational efficiency and proven efficacy in real-time motor imagery tasks.

Integration with Game Systems To bridge classified EEG commands with game controls, two primary approaches emerge:

- Keyboard emulation (e.g., via Python's pynput.keyboard library)
- Inter-process communication (e.g., socket-based implementations, as demonstrated by [88])

Game Development Platform Unity Engine is the predominant choice and is particularly suited for novice developers due to its intuitive, user-friendly interface and rapid prototyping capabilities for both 2D and 3D games.

5.2 A Guide to Design A Comprehensive EEG Game Performance Metric

A thorough assessment of the system should encompass both system performance and user experience, so we recommend using both quantitative and qualitative performance metrics.

Quantitative Performance Metric Quantitatively, we recommend researchers employ the following metrics:

- **Classification Accuracy** assesses the algorithmic performance of the EEG signal processing pipeline.
- **Game Score** can be used as a standardized performance measure. While the calculation varies across game genres, this metric provides a direct quantitative assessment of the system.
- **Control Effectiveness Score** evaluates the control effectiveness of EEG-based game control in a more comprehensive way. This metric should incorporate game-specific parameters through mathematical formulations. An example of this is the coin cluster approach in [62] and the CoinError metric in [12].

For comprehensive quantitative evaluation frameworks, researchers may consult [12, 88, 13].

Qualitative Performance Metric Qualitative performance metrics should be used to evaluate the usability of EEG-controlled game systems and gather valuable user feedback. These insights are essential for improving both the game experience and overall system design. Established questionnaires such as the GEQ, SUS, and NASA-TLX offer comprehensive sets of questions that assess various aspects of user experience, including engagement, usability, cognitive workload, and satisfaction. Researchers could refer to [13, 84, 75] for reference on qualitative performance metrics.

5.3 Trends and Challenges of EEG-Controlled Games

The current state of EEG-controlled games faces several fundamental limitations that impact both design and user experience. First, practical implementations typically limit the number of distinct mental tasks to 2-4 to maintain optimal classification accuracy. This limitation, coupled with the predominant research focus on signal classification rather than player experience and entertainment value, results in systems that function more as experimental platforms than engaging games. The challenge is particularly acute given that most EEG researchers lack formal training in game design principles. For theoretical frameworks on enhancing player engagement, we recommend consulting [61], while [13] provides a practical example of improved user experience design.

A critical gap in current research is the systematic evaluation of system usability and user experience. As evidenced by our review, few studies incorporate qualitative metrics alongside quantitative performance measures. We strongly advocate for comprehensive evaluation frameworks that assess both technical and human-centered dimensions of EEG gaming systems.

The significant variation in game scores across reviewed studies (Figure 5) highlights another challenge: unlike classification algorithms that can be uniformly assessed through accuracy metrics, game systems lack standardized evaluation criteria. This underscores the need for future research to establish quantitative benchmarks for game performance assessment.

The inherent latency of EEG signal processing presents a crucial constraint. Unlike keyboard inputs with sub-millisecond response times, EEG classification requires signal intervals rather than instantaneous measurements. Our analysis of Table 5 reveals typical latencies ranging from 1 to 3.5 seconds, making these systems unsuitable for fast-paced interactions but potentially viable for turn-based or slow-paced gameplay scenarios.

5.4 Limitation and Future Work

The major limitation is the lack of standardized evaluation methods across studies. This paper assess performance using in-game scores or task-specific metrics, which are not comparable enough between games. As a result, it is difficult to determine which game designs or control methods are most effective. Future research should aim to establish common evaluation criteria that incorporate both objective performance measures and subjective user experience. This would enable meaningful comparisons across studies and help identify best practices in the development of EEG-controlled games.

6 Conclusion

This systematic review has synthesized current research on EEG-controlled directional games, highlighting key methodologies, performance metrics, and persistent challenges in the field. Our analysis reveals that while motor imagery-based systems using CSP and LDA remain dominant for their real-time efficiency, significant limitations persist—particularly in system latency (1-3.5s), command diversity (optimally 2-4 classes), and evaluation standardization. Crucially, we identified a disconnect between technical optimization and entertainment value, with most studies prioritizing classification accuracy over user experience. To advance the field, we propose two critical directions for future work: (1) development of standardized, multimodal evaluation frameworks that balance quantitative performance with qualitative user experience metrics; and (2) improved game design strategies that leverage EEG's constraints (e.g., turn-based mechanics for latency tolerance). The transition from laboratory prototypes to consumer-ready applications demands equal attention to technical robustness and player satisfaction. By addressing these challenges, EEG-controlled games can evolve beyond research tools into viable entertainment platforms, unlocking new possibilities for accessible, immersive BCI gaming.

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7 Appendix

Table 6. Summary of Key Statistics from Reviewed Studies

Paper	**Number of Electrodes**	**Signal Preprocessing**	**Feature Extraction**	**Classifier**	**Accuracy**	**Average Game Score**	**Quantitative Performance Metric**	**Qualitative Performance Metric**	**Mental Task**	**Game**	**latency (sec)**	**Game Engine**
[12]	8	bandpass filter	CSP	LDA	None	32.24%	Score, Coin-Error(CE)	Self designed questionnaires	left/right hand, and no MI	Collecting coins in three lanes	NM	Unity
[88]	27	bandpass filter	CSP	LDA	70%	None	game score, SMR and TBR, a formula for sense of control	None	left/right hand	Keep a ball from falling off the platform	NM	Qt creator
[39]	40	power frequency filtering, EOG extraction, and baseline correction of EEG	ICA, CSP	SWNN	None	None	Score, ERD and ERS	None	left/right hand, feet, tongue, single/double blink	3D Tetris	1.43	None
[62]	5	bandpass filter	None	LDA	None	65.80%	Score, Coin Clusters Collected, Accuracy	None	left/right hand, blink	Collecting coins in three lanes	NM	Unity
[13]	8	bandpass filter	CSP	LDA	None	36.57%	CE	SUS, NASA-TLX	left/right hand	Collecting coins in three lanes	NM	Unity
[63]	4	bandpass filter	None	MLP	None	59%	Score, Coin Clusters Collected, Accuracy	None	left/right hand, blink	Collecting coins in three lanes	3	Unity
[84]	8	None	CSP	LDA	63.19%	None	Score	VMIQ2, GD, NASA TLX, GEQ, SUS	left/right hand	Rowing a boat to collect flags	NM	Unity
[?]	8	a self-designed spatial filter + bandpass filter	None	LDA	65%	65%	Accuracy	None	left/right hand	Collecting fruits on trees alongside a path	NM	Unity
[41]	16	None	CSP	LDA	70%	70%	Accuracy	None	left/right hand, both feet, tongue	Maze	NM	NM

Table 7. Table 6 Continued

Paper	Number of Electrodes	Signal Preprocessing	Feature Extraction	Classifier	Accuracy	Average Game Score	Quantitative Performance Metric	Qualitative Performance Metric	Mental Task	Game	latency (sec)	Game Engine
[50]	8	python and MNE library, bandpass filter	FIR	LSTM, CNN	72% and 70%	72% and 70%	Accuracy	None	left/right hand, head movement	Super Mario game	NM	None
[11]	3	Filter Bank (FB) composed by an array of bandpass filters	CSP	NBPW	74%	74%	Accuracy	Self designed questionnaire on a 7-point Likert scale	left/right hand	Sliding a ball toward a given target	2	Unity
[75]	20	bandpass filter	FFT, CSP	LDA	58.30%	58.30%	Accuracy	NASA TLX, a self-designed questionnaire	left/right hand	using the cued hand to push a button	3.5	Untiy
[76]	28	None	FFT, CSP	LDA	None	67.11%	Score, Accuracy, BTR, ERD	self designed quetionnaire on a Likert scale	left/right hand	Destroying Asteroids	customizable	Unity
[20]	64	None	ICA	SVM	76%	76%	Accuracy	None	left/right hand	Choosing from two objects to place on a trash bin	NM	NM
[36]	32	bandpass filter	CSP	RLDA	90%	90%	Accuracy	None	left/right hand, feet, relax	A car racing game	1-2	Unity
[86]	20	bandpass filter	CSP	LDA	87.01%	87.01%	Accuracy, TPR, FPR	None	left/right hand+SSVEP	2D tetris	2 sec	NM
[45]	9	None	BP, CSP	LDA	None	None	None	None	left/right hand	Rotating shapes to solve puzzles	1 sec window every 1/16 sec	UE4