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TOPICAL REVIEW

Neurotechnology in Gaming: A Systematic Review of Visual Evoked Potential-Based Brain–Computer Interfaces

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ABSTRACT Brain-computer interfaces (BCIs) have received considerable attention in gaming, enabling innovative interactions with digital environments. Visual Evoked Potentials (VEPs)—robust, noninvasive neural responses to visual stimuli—offer high information transfer rates, making them particularly promising. This systematic review, guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, examines VEP-based BCIs in gaming. We searched the Web of Science and Google Scholar, identifying 16 347 studies from the past decade, with 46 selected for in-depth analysis after rigorous screening. The review explores VEP response modeling, electroencephalography (EEG) signal acquisition and processing, stimulation paradigms, and their gaming applications. These systems enhance accessibility for players with physical or cognitive impairments, support adaptive difficulty scaling, personalize gameplay, aid neurorehabilitation, and enable multiplayer interactions. However, challenges remain, including technical limitations, complex data interpretation, user adaptability, and ergonomic issues. Advances in signal processing, personalized calibration, and hybrid multimodal approaches could improve usability. Future research should focus on integrating VEP-based BCIs with emerging technologies, optimizing user comfort, and developing adaptive interaction models to enhance immersion and accessibility. By addressing these challenges and utilizing neuroscience and computational advancements, VEP-based BCIs promise to transform gaming into a more inclusive and immersive experience for diverse users.

INDEX TERMS Brain–computer interfaces, visual evoked potentials, signal processing, neurotechnology, gaming accessibility, electroencephalography, virtual reality, augmented reality, machine learning, neurorehabilitation.

I. INTRODUCTION

By analyzing cerebral activity without requiring muscular movements, brain-computer interfaces, or BCIs, allow direct communication between the human brain and external equipment [1], [2], [3], [4], [5]. Initially developed to assist individuals with severe motor impairments caused by conditions like amyotrophic lateral sclerosis (ALS) or spinal cord injuries, BCIs have evolved significantly over the past few decades [1], [4], [6]. Advances in neuroscience, signal processing, and machine learning have expanded their applications beyond medical rehabilitation to include areas such as education, entertainment, and human-computer interaction [1], [2], [3], [7].

BCI systems commonly employ various neuroimaging modalities, including electroencephalography (EEG) [8],

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[9], functional near-infrared spectroscopy (fNIRS) [10], [11], functional magnetic resonance imaging (fMRI) [12], [13], [14], and magnetoencephalography (MEG) [15], [16]. Among the various modalities, EEG is the most used due to its portability, affordability, and user-friendliness, as shown in Table 1 [9], [17]. Three common paradigms of EEG signals - event related potentials (ERP) [18], [19], sensorimotor rhythms (SMR) [20], [21], [22], and visual evoked potentials (VEP) [23], [24], [25] are utilized in analyzing brain activities, and Figure 1 illustrates the significant rise in interest in EEG-based BCI in the last 10 years as reflected in the increasing number of publications employing various paradigms.

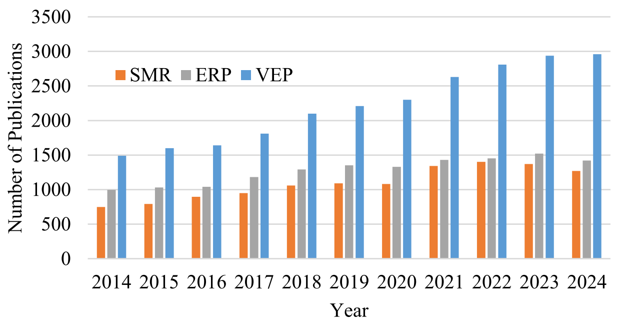

FIGURE 1. **Distribution of published studies across different subfields of EEG-based BCI systems, based on search results from Google Scholar.**

Among the various BCI paradigms, VEP-based BCIs have attracted significant interest due to their reliability, high information transfer rates, and non-invasive nature [26], [27], [28]. VEPs are electrical responses from the visual cortex evoked by visual stimuli [26], [29]. By presenting specific visual patterns or flickering lights to a user, VEP-based BCIs can decode the resulting neural responses to determine the user's intent in real time, making them particularly suited for applications such as video games [24], [30], [31], [32], [33].

Building on this foundation, several types of VEP-based BCIs have been developed, each employing distinct stimulation methods and offering unique advantages. These include Steady-State Visual Evoked Potentials (SSVEPs) [30], [43], [44], Code-Modulated VEPs (c-VEPs) [26], [31], Motion-Onset VEPs (m-VEPs) [24], [32], and transient VEPs (t-VEPs). For example, SSVEP-based BCIs rely on flickering visual stimuli at constant frequencies and are known for their high signal-to-noise ratio and minimal training requirements [30], whereas c-VEPs use coded sequences to modulate visual stimuli, enabling faster communication and greater resistance to interference [31].

Recent developments in the field have further expanded the capabilities of VEP-based BCIs, driving innovation in their application to gaming. Advanced signal processing algorithms, including machine learning and adaptive filtering, have improved the precision and reliability of VEP decoding [45]. Detailed neurofeedback systems now enable real-time monitoring and adjustment of VEP responses, allowing effective integration with mainstream gaming platforms [46]. Moreover, the integration of multi-modal sensor inputs, such as combining EEG with virtual reality (VR), has opened up immersive and hands-free navigation possibilities [47]. Personalization has also become a focus, with adaptive algorithms that dynamically adjust game parameters based on players' cognitive states, thereby optimizing engagement and satisfaction [48]. Finally, emerging neuroergonomic design principles are guiding the development of user-centric BCIs that accommodate cognitive workload, mental fatigue, and social dynamics [49], [50].

As a result of these advancements, integrating VEPs into video games represents a notable intersection of neuroscience and interactive media [24], [26], [31] (see Figure 2 for a schematic representation of a VEP-based BCI system in the area of video games). The gaming industry, which values innovation and immersive experiences, provides an ideal platform to apply BCI technologies. VEP-based BCIs can improve gaming by introducing new ways to control games, making them more accessible for players with physical disabilities [32], and creating unique game-play experiences that respond directly to a player's brain activity [51]. Furthermore, games incorporating BCIs hold therapeutic potential, such as cognitive training or neurofeedback interventions for individuals with attention deficit hyperactivity disorder (ADHD) [26], [51], [52], [53].

Despite their potential, several challenges hinder the widespread adoption of VEPs in gaming. Technical issues include the need for reliable and user-friendly EEG equipment, complexities in signal processing, and ensuring that systems respond quickly enough for seamless gameplay. User comfort and adaptability are also crucial, as prolonged exposure to certain visual stimuli can cause fatigue or discomfort [28], [30], [31], [32].

Considering the growth of VEP-based BCIs in gaming, a systematic review is essential to evaluate current applications, limitations, and future opportunities. The following subsection outlines the methodology used to identify and analyze relevant studies, ensuring a comprehensive and unbiased review of prior research.

The remainder of this paper is structured as follows: Section II provides a comprehensive overview of the principles and applications of VEP-based BCIs, including types of visual evoked potentials, EEG techniques for capturing VEPs, essential signal processing methods, and gaming applications. Section III focuses on the challenges and limitations associated with VEP-based BCIs in gaming, highlighting key technological and performance constraints such as signal reliability, latency, and hardware limitations. It also examines user adaptability and the learning curve of VEP-based interfaces, addressing concerns related to usability and long-term engagement. Section IV outlines future research directions and emerging trends in the field, discussing potential advancements in hardware, signal processing, and adaptive BCI frameworks. Section V presents a detailed

TABLE 1. The comparison of EEG and other modalities and paradigms.

Key Attributes	EEG			fNIRS [34]	fMRI [35]	MEG [36]
	VEP [37]	ERP [38]–[40]	SMR [41]			
ITR (bits/min)	50∼200	2∼50	5∼25	3.18∼8.23	∼5	13.1∼19.6
SNR (dB)	5∼20	0.87∼8.18	−16 ∼ 5	26.48∼31.93	1.07∼161.2	2∼35
User fatigue	High visual fatigue	Moderate cognitive load	Mental workload	Mild discomfort	Long sessions	Helmet discomfort
Cost	Low			Moderate	High	Very high
Temporal resolution [42]	∼0.05 s			∼1 s	∼1 s	∼0.05 s
Spatial resolution [42]	∼10 mm			∼5 mm	∼1 mm	∼5 mm
Risk	Non-invasive			Non-invasive	Non-invasive	Non-invasive

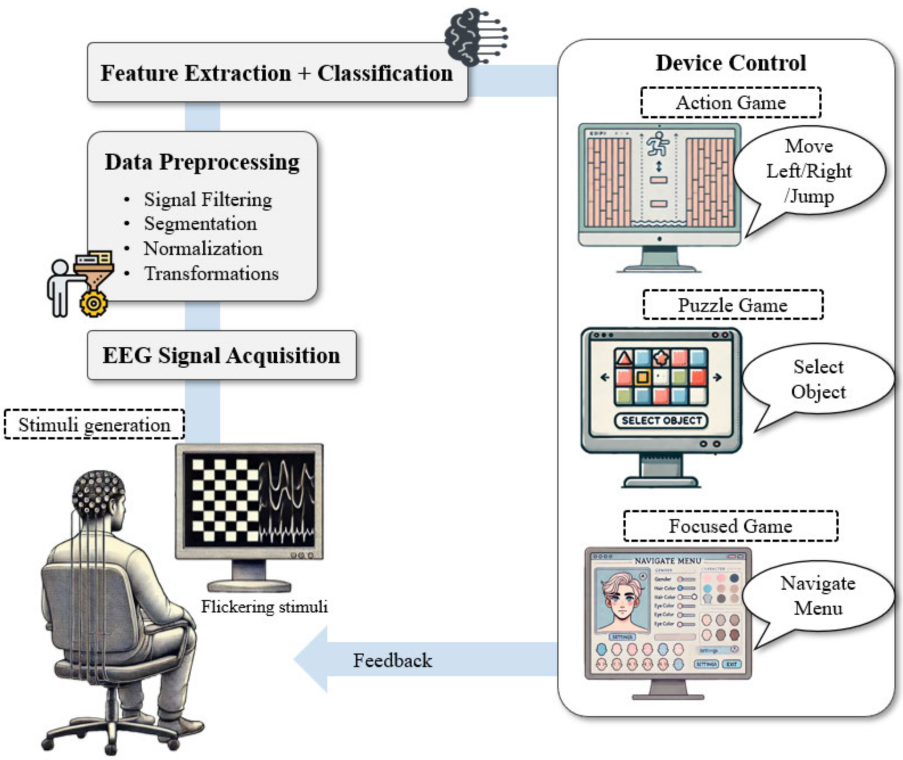

FIGURE 2. Schematic representation of a Visual Evoked Potential-based Brain-Computer Interface system integrated into video game applications.

discussion of the review findings, synthesizing current progress, unresolved limitations, and key open questions related to feasibility, performance, and inclusivity. Finally, Section VI summarizes the key insights and contributions of the paper.

A. STUDY SELECTION PROCESS

We conducted this literature review in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [54]. To ensure a comprehensive overview of the application of VEP-based BCIs in gaming, a systematic search strategy was employed across the Web of Science database and Google Scholar search engine.

A combination of relevant keywords and Boolean operators was used to capture the breadth of VEP-based BCI research in gaming contexts:

- "VEP" OR "SSVEP" OR "c-VEP" OR "m-VEP" AND "BCI" AND "EEG"
- "Visual Evoked Potentials" AND "Brain-Computer Interface" AND "Gaming"
- "Steady-State Visual Evoked Potentials" OR "SSVEP" AND "Video Games"
- "EEG-Based BCIs" AND "Interactive Applications"

To ensure the quality and relevance of the studies, the following criteria were applied:

1) **Inclusion Criteria:**

- Studies focusing on VEP-based BCIs in gaming contexts.
- Peer-reviewed journal articles, conference proceedings, or book chapters.
- Studies published in English.

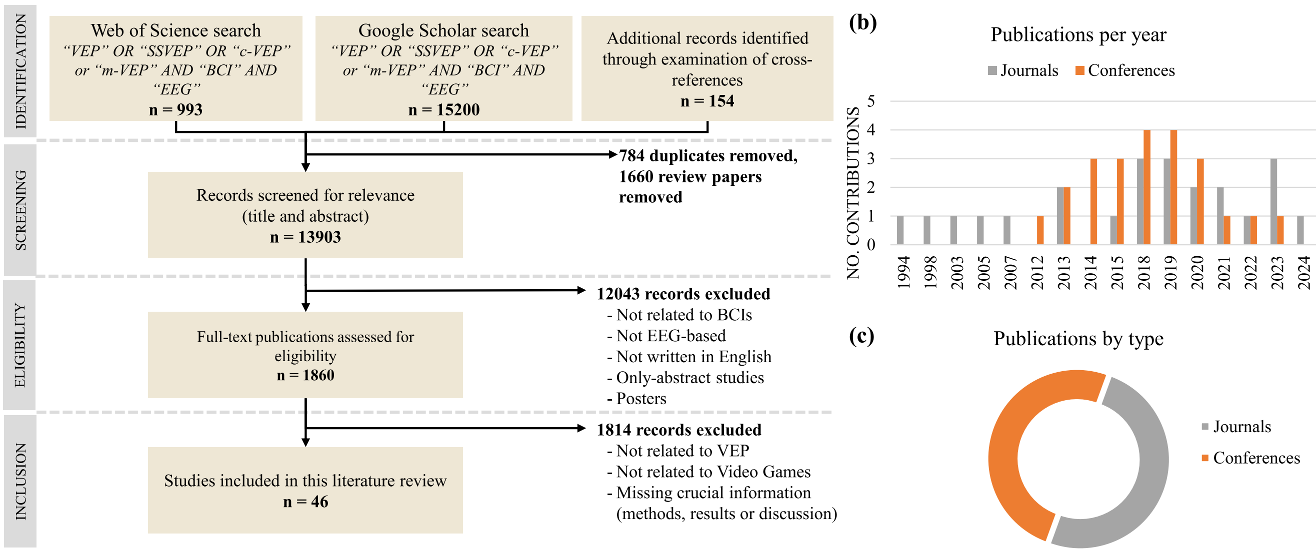

FIGURE 3. (a) Flowchart of the study selection process as carried out in accordance with the PRISMA guidelines. (b) Distribution of selected VEP-related publications per year between 1994 and 2024. (c) Number of VEP-related journals and conferences included in the literature review.

- Research presenting experimental results, technological developments, or application reviews.

2) **Exclusion Criteria:**

- Studies focusing exclusively on other BCI paradigms (e.g., motor imagery or P300).
- Non-peer-reviewed articles, abstracts, posters, or editorials.
- Articles lacking methodological detail or relevance to gaming applications.

The search initially yielded a total of 16347 records across all databases from the past 10 years. After removing 784 duplicates and 1660 review papers, 13903 unique studies remained for screening. Initial screening of titles and abstracts excluded 12043 records, resulting in 1860 studies for further evaluation. Following a preliminary full-text assessment, 1087 additional records were excluded (e.g., not using EEG signals or not published in English), resulting in 773 studies selected for comprehensive review.

Subsequent in-depth analysis led to the exclusion of 727 additional records—238 for not being strictly related to BCIs or lacking sufficient methodological detail, and 489 for not incorporating VEP-based approaches or relevant gaming components. This yielded a final set of 46 studies that met all inclusion criteria (see Figure 3 for the PRISMA flowchart).

II. VEP-BASED BCIs: PRINCIPLES AND APPLICATIONS

Visual evoked potentials (VEPs) are one of the most commonly used signals in non-invasive BCIs due to their reliability and capacity to enable rapid information transfer [23], [26], [27], [28]. By presenting visually stimulating cues—such as flickering images or coded patterns—and measuring the corresponding cortical responses via EEG, researchers can achieve real-time control in interactive applications, particularly in video gaming [24], [26], [31].

The primary types of VEPs, which are compared in Table 2, include:

- Steady-State Visual Evoked Potentials (SSVEPs): Triggered by continuous flickering stimuli; ideal for high-speed control in gaming.
- Code-Modulated VEPs (c-VEPs): Use coded sequences to enhance reliability against noise and interference.
- Motion-Onset VEPs (m-VEPs): Triggered by dynamic changes in visual input; useful for immersive and VR-based gaming.
- Transient VEPs (t-VEPs): Generated by sudden changes in stimuli; applicable to discrete, action-based gaming.

To effectively integrate VEP-based BCIs into gaming, it is essential to understand their physiological basis and practical implementation. This section begins by explaining how visual stimuli are processed in the brain and reflected in EEG recordings. It then outlines the EEG instrumentation and protocols necessary for reliable VEP acquisition, including hardware considerations, electrode placement, and signal integrity requirements. Next, we examine the core VEP paradigms—SSVEP, c-VEP, m-VEP, and t-VEP—highlighting their underlying mechanisms, relative advantages, and trade-offs in terms of information transfer rate (ITR), user training burden, and visual comfort. In addition to traditional paradigms, this section also explores novel approaches to reducing visual fatigue and improving immersion. These include multimodal and hybrid interfaces that combine VEPs with other input modalities, allowing for more adaptive gaming experiences.

While understanding the physiological foundations of VEPs is vital, effective brain-computer interaction also

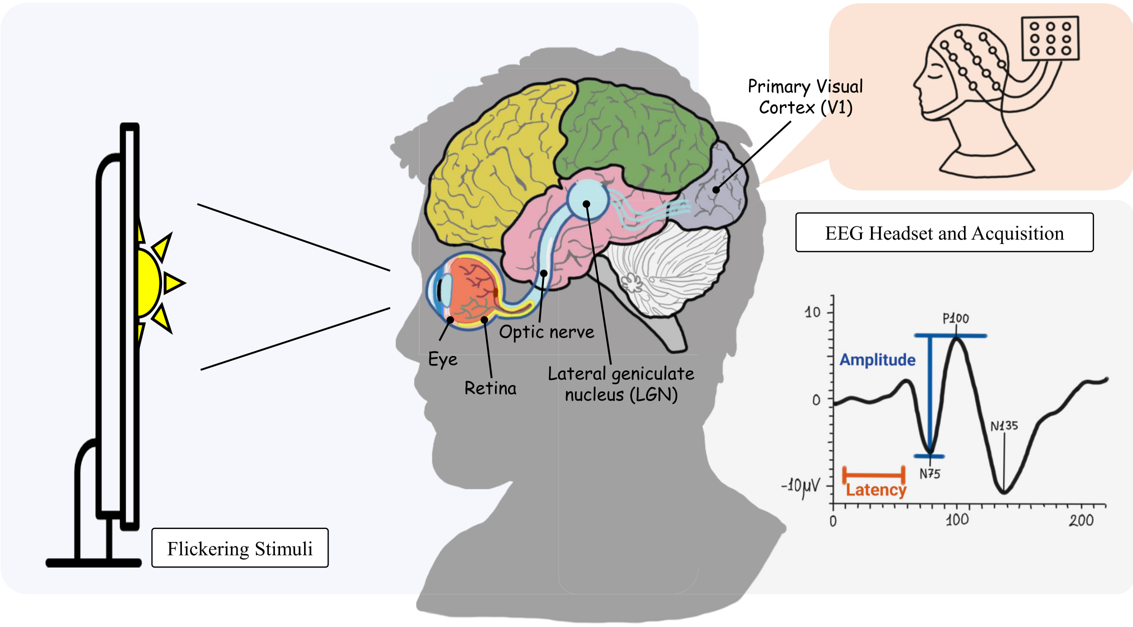

FIGURE 4. Schematic representation of the VEP generation and acquisition process. Visual stimuli, such as flickering light patterns, are processed as they travel from the retina to the lateral geniculate nucleus (LGN) through the optic nerve and finally to the primary visual cortex (V1), emphasizing the latency and localization of neural responses.

TABLE 2. Comparison of VEP paradigms for gaming applications.

VEP Type	Response Type	Information Transfer Rate	User Fatigue	Suitable Game Genres
SSVEP	Continuous, frequency-specific	High	High	Action, RTS
c-VEP	Code-correlated	High	Low	Competitive, Simulation
m-VEP	Dynamic, parietal response	Medium	Low	VR, AR, Exploration
t-VEP	Transient	Medium	Low	Point-and-click games

depends on robust signal processing techniques. The next section addresses the technical aspects of signal handling, including preprocessing (e.g., artifact removal), feature extraction methods, and classification algorithms that form the foundation for reliable command execution in gaming environments.

A. OVERVIEW OF VISUAL EVOKED POTENTIALS (VEPs)

Visual Evoked Potentials play a key role in the understanding of visual processing and serve as the basis for developing BCIs. They are electrical signals produced in the visual cortex in response to visual stimuli. When light enters the eye, it activates the retina, which sends neural signals through the optic nerve to the lateral geniculate nucleus and then to the primary visual cortex (V1) located in the occipital lobe of the brain [26], [55], [56] (see Figure 4). This neural pathway is essential for visual perception, and the VEPs produced along this route reflect how the brain interprets visual inputs.

VEPs appear as synchronized waveforms that can be measured at occipital scalp sites, such as Oz, O1, and O2, using the international 10–20 EEG system [26], [57]. Their amplitude and latency depend on the features of the visual stimulus (e.g., intensity, pattern, frequency) and on individual cognitive factors like attention [29], [58]. These waveforms often include identifiable components, such as the P100, which appears approximately 100 ms post-stimulus, providing insights into the timing of visual processing [59].

VEPs typically possess a high signal-to-noise ratio (SNR) compared to other EEG-based methods, simplifying real-time detection [23], [24], [25]. This elevated SNR is primarily due to the time-locked nature of VEP responses to stimulus onset, which enables the application of signal averaging across trials to improve non-phase-locked background EEG noise [60], [61]. Additionally, the high reproducibility of VEPs—stemming from consistent activation of neural generators in the visual cortex in response to identical stimuli—further enhances signal clarity. Averaging these stable, evoked responses amplifies the signal while diminishing trial-to-trial noise variability [42], [62].

Beyond physiological factors, recording quality plays a critical role in maximizing SNR. The use of low-impedance electrodes and high-gain differential amplifiers reduces external interference, while advanced digital signal processing techniques—such as Fourier analysis and spatial filtering—enable robust extraction of VEPs from noisy EEG signals [63]. These capabilities are particularly important in gaming contexts, where fast and accurate control is important [64], [65], [66].

Moreover, optimizing stimulus parameters—for example, contrast, luminance, and temporal frequency—can further enhance VEP amplitude while minimizing extraneous neural activity. This optimization, in combination with the benefits of signal averaging, makes VEPs well-suited for interactive gaming applications. Paradigms such as SSVEP [30], [43], [44] and c-VEP [31] are particularly effective, offering high information transfer rates by associating distinct visual stimuli with frequency- or phase-specific responses. This enables rapid execution of user commands, thereby enhancing system responsiveness. Furthermore, the rapid onset and offset of VEPs allow for near-instantaneous feedback loops, as cortical responses can be analyzed within milliseconds of stimulus presentation [57], significantly improving immersion and interactivity in gameplay.

Despite these advantages, VEP-based BCIs depend heavily on consistent visual engagement, making them less suitable for individuals with visual impairments or tasks that require attention to non-visual elements [26], [51], [52], [53]. Any lapse in visual focus can degrade signal quality and reliability [67]. Furthermore, the flickering stimuli commonly employed—particularly in SSVEP setups—can lead to eye strain or visual fatigue over extended periods, potentially reducing user comfort and limiting the practicality of long-term gaming sessions [1], [28].

B. EEG AS A TOOL FOR CAPTURING VEPs

Electroencephalography is the primary non-invasive methodology for recording VEPs, enabling real-time mapping of cortical responses to visual stimuli [8], [9], [18], [20], [68]. By placing electrodes on the scalp, EEG monitors subtle, time-locked fluctuations in neural activity, translating them into actionable commands for interactive applications, including gaming and rehabilitation (see Figure 5) [5], [9], [59].

Optimal electrode placement significantly influences EEG effectiveness in capturing VEP signals. Typically, electrodes are placed according to the international 10–20 system, primarily centered over the occipital cortex at positions O1, Oz, and O2, due to their proximity to the primary visual cortex (V1). These locations consistently produce strong, high-amplitude signals essential for rapid and reliable response detection [23], [69]. Additionally, electrodes situated in parietal and temporal areas (POz, Pz, PO3, PO4) enhance the detection of supplementary visual processing activities, such as attentional adjustment and motion responses [24], [70]. For tasks requiring high precision, advanced EEG setups with dense electrode arrays (32–128 channels) can significantly improve spatial resolution and signal reliability [67], [71].

Temporal coordination between visual stimuli and EEG recordings is essential to ensure accurate synchronization of the data collected during experiments [23], [67]. Proper timing ensures precise correlation between stimuli and neural responses, significantly affecting detection accuracy and latency—both of which are critical parameters in interactive applications like gaming. Therefore, precise stimulus intervals and clearly defined response windows must be carefully calibrated to optimize system responsiveness and user experience.

Another critical factor influencing EEG efficacy is the choice of reference and ground electrodes. Commonly, mastoid (A1, A2) or earlobe locations are selected for reference electrodes due to minimal cortical activity interference, facilitating clear interpretation of VEP signals [27], [67]. Ground electrodes, typically positioned at neutral locations such as Fpz, further stabilize EEG recordings by reducing electrical noise. Certain methods, including c-VEP or m-VEP, may expand electrode coverage to the parieto-occipital boundary to capture specific signals related to motion and phase variations.

Common EEG sampling rates range from 256 to 512 Hz or higher to capture both transient and steady-state components of VEPs, while the amplifier bandwidth typically covers 0.1–100 Hz to accommodate both low- and mid-frequency components of SSVEPs. Although clinical-grade EEG systems deliver superior signal fidelity and strong noise suppression, portable or consumer-grade headsets have gained popularity for gaming applications due to their ease of deployment and lower cost [72]. However, these portable devices may require more frequent calibration and advanced artifact handling to maintain adequate signal quality over time [72].

Maintaining a high SNR is crucial for the reliability of VEP-based BCIs. Although EEG signals inherently exhibit a low SNR due to the small amplitude of neuronal potentials—which can easily be contaminated by artifacts such as eye blinks, muscle contractions, and ambient electrical noise [42]—VEPs generally possess a relatively higher SNR compared to other EEG-based paradigms [23], [24], [25]. To further enhance the SNR, advanced filtering techniques, including independent component analysis (ICA) and wavelet-based denoising, are employed to effectively isolate and remove non-cortical artifacts [5]. Additionally, participants are instructed to minimize movement and blinking during critical stimulus intervals, which significantly improves EEG recording quality and ultimately enhances the accuracy and responsiveness of VEP-based BCIs [60], [69], [73], [74].

Electrode density significantly influences EEG performance by affecting both spatial resolution and user comfort. High-density EEG systems (64–128 channels) offer superior spatial resolution beneficial for precise cognitive tasks and research-intensive applications; however, these systems may be impractical for prolonged or frequent use due to increased user discomfort, complexity of setup, and higher resource demands [75]. Conversely, low-density EEG configurations (8–32 channels) enhance user comfort, reduce setup time, and provide greater practicality for everyday

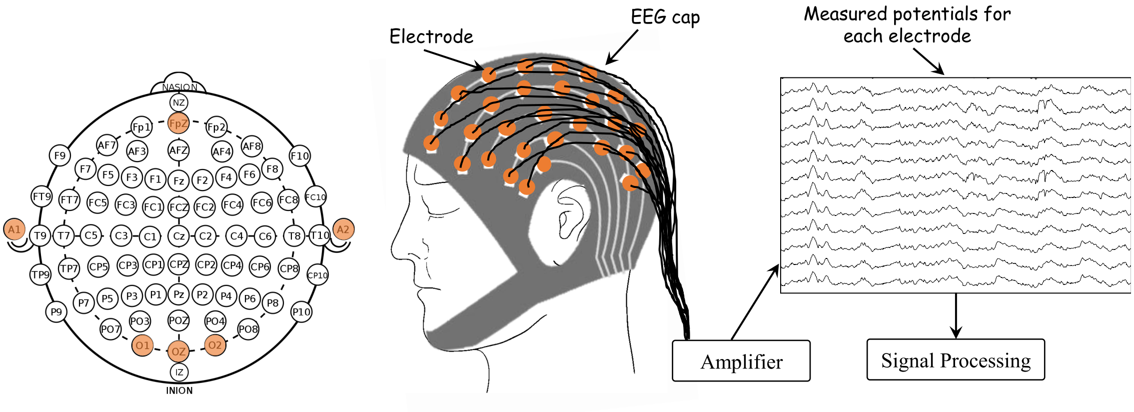

FIGURE 5. Schematic of a typical EEG recording setup for VEP-based BCIs. The diagram on the left illustrates the standard 10–20 electrode placement system, emphasizing the occipital sites (O1, Oz, O2), which are most relevant for capturing VEPs. It also highlights common reference electrodes (A1, A2), typically placed on the left and right mastoid processes, as well as the ground electrode (Fpz), often located on the forehead. An EEG cap with multiple electrodes records scalp potentials, which are then amplified and processed to extract meaningful signals for subsequent BCI applications.

applications, albeit at the expense of spatial resolution [76]. Recent advancements in signal processing and machine learning techniques have partially compensated for these spatial resolution limitations, thus improving the effectiveness of low-density EEG setups in gaming and clinical contexts [77].

Achieving an optimal balance between electrode density and usability is essential for VEP-based BCIs, especially in gaming scenarios. For example, SSVEP-based BCIs can effectively operate with as few as 4–8 electrodes because they primarily utilize frequency-domain analysis rather than precise spatial localization [78]. Such low-density setups are advantageous in gaming environments where real-time responsiveness and ease of use are crucial. However, higher electrode densities may be necessary for applications requiring more accurate recordings of brain activity, such as monitoring complex cognitive states like emotion or implementing adaptive difficulty in gaming. Ultimately, the choice of electrode density in VEP-based BCI systems depends on the specific balance desired between signal quality and user experience. Low-density systems are generally more suitable for gaming applications prioritizing comfort, usability, and immediate interaction, despite the higher precision available with high-density EEG setups.

Beyond electrode configuration, practical considerations in user comfort and ease of setup significantly influence EEG adoption. Traditional gel-based electrodes, though providing stable signals, can be uncomfortable and time-consuming to prepare. Alternatively, dry electrodes offer faster setup times and enhanced comfort but typically introduce higher noise levels, particularly in users with dense hair [72]. Advances in lightweight, ergonomic headgear and automated calibration procedures enhance user comfort and accessibility, encouraging broader adoption in interactive and therapeutic environments [42], [79].

Ultimately, achieving optimal EEG-based VEP recording involves careful balancing of spatial and temporal electrode coordination, selection of appropriate electrode density and type, and robust artifact management strategies. Addressing these considerations collectively ensures reliable, comfortable, and effective EEG implementations in gaming and rehabilitation contexts, paving the way for broader practical adoption [80].

C. TYPES OF VEPS AND THEIR RELEVANCE TO GAMING

VEPs are signals of electric form produced in the visual cortex as a reaction to visual stimuli [27], [67], [81]. In BCIs for gaming, these responses must not only be robust and fast but also comfortable over extended periods of play [65], [66]. Here, we propose a classification of VEP paradigms with specific relevance to gaming applications. This grouping categorizes VEPs into three broad classes based on the nature of the visual change and the demands of the gaming environment: (1) high-speed, continuous control VEPs; (2) discrete, action-triggered VEPs; and (3) low-fatigue, immersive or multimodal VEPs.

1) HIGH-SPEED, CONTINUOUS CONTROL VEPs

Fast-paced games, such as racing simulators and real-time strategy games, require rapid and continuous BCI input. In this category, methods that produce continuous, frequency–locked responses are ideal.

Steady-State VEPs (SSVEP) serve as a prime example, as they are induced when a visual stimulus flashes at a fixed frequency f, typically ranging between 6 to 15 Hz [1], [47], [75], [82], [83], [84], [85], [86], [87], [88]. This generates neural oscillations in the visual cortex matching the fundamental frequency f and often its harmonics $2f, 3f, \ldots$ [75], [84], [88]. The periodic nature of SSVEPs enables the extraction of distinct frequency components from the EEG signal, allowing for reliable classification of user intentions based on the detected frequencies [86]. Mathematically, the recorded EEG response in an SSVEP-based system can be approximated by:

$$x(t) \approx Asin(2\pi ft) + \sum_{n=2}^{N} \alpha_n sin(2\pi nft + \phi_n), \tag{1}$$

where A and α_n are amplitude factors, and ϕ_n represents phase offsets for each harmonic.

To elicit distinct responses, multiple flickers can be displayed simultaneously, each at a unique frequency $\{f_1, f_2, \ldots, f_K\}$. When a user fixates on a specific flicker, the strongest sinusoidal component in the EEG spectrum appears at that flicker's fundamental frequency [82], [84]. In practical target identification, the magnitude of the power of the EEG signal at each flicker frequency is compared to the average power in the nearby frequency bands [1]. This comparison provides a measure of how pronounced (or "clean") the signal is at that particular frequency. The flicker whose frequency yields the highest ratio of signal power relative to the surrounding noise is then selected as the target, indicating the user's choice.

Common stimulus designs for SSVEP paradigms include checkerboard flickers—alternating black and white patterns that oscillate at predetermined frequencies—and direct LED or screen flicker, in which specific regions or lights flash at designated frequencies to evoke distinct SSVEP responses [47], [83]. In applications requiring multiple choices, different flicker frequencies (frequency tagging) can be assigned to each option within the interface, enabling users to select a target simply by fixating on the stimulus corresponding to their desired frequency [84].

SSVEP-based BCIs are particularly well suited for fast-paced gaming environments that demand rapid and continuous user input. For example, in action or racing games, these systems can translate the user's focus on distinct flickering stimuli into immediate control commands, thereby supporting swift movement and decision-making [1]. The inherently high ITR associated with SSVEPs enables rapid command execution, which can significantly enhance the overall gaming experience [37]. However, the continuous presentation of flickering stimuli may induce visual fatigue or discomfort during prolonged gameplay, potentially impacting user engagement [71].

Similarly, **Code-Modulated VEPs (c-VEPs)** are generated using visual stimuli that are modulated by specific codes, such as pseudo-random binary sequences [31], [89]. These codes help in distinguishing the brain's responses to different stimuli, enabling robust signal decoding even in environments with high noise levels. Among these, the *m*-sequence is the most commonly used pseudo-random sequence. A binary *m*-sequence is generated through maximal linear feedback shift registers, which possess several characteristics that make them useful for analyzing both linear and nonlinear systems [31]. Notably, an *m*-sequence has an autocorrelation function that closely approximates a unit impulse function and is nearly orthogonal to its time-lagged sequence. This property enables the use of an *m*-sequence and its time-lagged variant in c-VEP-based BCI systems.

Each stimulus target is driven by a unique binary sequence over a stimulation cycle, synchronized with a trigger for precise EEG alignment. During training, the user fixates on a known target for N cycles, and the averaged EEG produces a template $T(t)$. If the user's attention shifts to another target k, the recorded signal can be correlated with a time-shifted version of $T(t)$, denoted $T_k(t)$ [26].

$$\rho_k = \frac{T_k x^T}{\sqrt{(T_k {T_k}^T)(xx^T)}}. \tag{2}$$

The correlation coefficient is computed, and the target with the highest correlation is identified. One of the most notable c-VEP-based BCI systems was introduced by Sutter [90], achieving an impressive communication rate of 10 to 12 words per minute (exceeding 100 bits/min). However, in the last decades, research on c-VEP remained limited, and the performance of subsequent systems was often unsatisfactory. For instance, Momose [91] developed a c-VEP BCI system with four targets, but it required five seconds to identify a target, resulting in a communication rate of less than 20 bits per minute.

c-VEPs have reduced flicker sensitivity, which can minimize visual discomfort and fatigue, enhancing user comfort during extended gameplay. They also support rapid command switching, making them suitable for games with multiple actionable items and dynamic environments. In terms of reliability, the coded signals are generally more resilient to noise and artifacts, improving classification accuracy and reliability in diverse gaming conditions [89].

In addition, **Frequency VEPs (f-VEPs)**—which assign a unique frequency to each control option—are also well suited to this category; their frequency-specific responses enable rapid and robust command differentiation without requiring complex user training [67]. In an f-VEP-based BCI, each target is presented at a unique frequency, producing a periodic sequence of evoked responses that match the fundamental frequency of the stimulus as well as its harmonics [92].

Since the flicker frequency in f-VEP BCIs is typically above 6 Hz, the evoked responses from consecutive flashes overlap, forming a periodic pattern of VEPs known as SSVEPs, which are synchronized with the flickering target. For this reason, f-VEP BCIs are often classified as SSVEP BCIs. Their key advantages include a non-complicated system setup, minimal or no user training, and a high ITR ranging from 30 to 60 bits per minute.

Together, these methods are most appropriate when the BCI is used for continuous control during high-intensity gaming, where speed and precision are crucial.

2) DISCRETE, ACTION-TRIGGERED VEPs

Many gaming applications involve discrete actions or commands (e.g., jumping, shooting, or selecting a menu option) rather than continuous control. For these applications, transient VEPs that are time-locked to a specific event are preferable. **Transient VEPs (TVEPs)** are triggered by abrupt visual onsets or offsets, such as a flashing stimulus that appears or disappears quickly and provide clear, time-specific markers that can be associated with individual game actions. The resulting waveform often includes distinct components like P100 or N100 within the first 200 ms [55]. A common approach is to define a narrow time window (e.g., 0–300 ms) following stimulus onset. The amplitude around the known latencies of P100 (80–120 ms) or N100 (120–180 ms) is measured, or a correlation with a transient response template is performed. Detection can be simplified by thresholding:

$$A_{P100} = \max_{t \in [80, 120ms]} x(t). \tag{3}$$

If A_{P100} exceeds a predefined value, the system registers the event. TVEPs are often limited to simple, binary decisions to avoid fatigue caused by continuous flashing [93], [94]. They are ideal for scenarios where quick, single-event responses are required, making them suitable for cue-based control systems in gaming. Moreover, they can be employed to detect moments of user attention or focus, allowing for context-sensitive interactions within the game. However, TVEPs have low SNR, where single-event responses may be less robust against noise, requiring techniques such as signal averaging or advanced detection algorithms to improve reliability [93], [94], [95]. In addition, TVEPs typically convey less information per event compared to steady or coded paradigms, potentially limiting their utility in high-complexity gaming environments.

Within this group are also the **Pattern Reversal VEPs (PR-VEPs)**—triggered by alternating visual patterns, such as checkerboards switching between black and white. The waveforms of PR-VEP (notably N75, P100, N135) are widely used in clinical diagnostics due to their reliability and stable latencies [96]. However, they have a lower ITR, limiting their use in research-oriented or diagnostic gaming applications. A typical method alternates the checkerboard every 125–1000 ms. The EEG epochs following each reversal are averaged, reducing noise and revealing the characteristic PR-VEP peaks [97]. A threshold on the P100 amplitude can serve as an indicator of user intent. Due to the slower nature of pattern reversals, PR-VEPs may achieve lower information transfer compared to fast flicker-based approaches [98].

Likewise, **Motion-Onset VEPs (m-VEPs)** arise when a static display introduces sudden motion, engaging both occipital and parietal areas that specialize in motion and spatial processing [24]. Changes in velocity or direction can likewise elicit robust event-related responses [33]. In practice, objects within a display move or alter their trajectories at predetermined intervals, producing time-locked epochs in the EEG [32]. Short segments (e.g., 0–300 ms post-motion onset) are extracted and analyzed for characteristic peaks (e.g., N2) or for correlation against a learned m-VEP waveform:

$$\rho_{mVEP} = \frac{\sum_{t=1}^{T} x(t)M(t)}{\sqrt{\sum_{t=1}^{T}[x(t)]^2 \sum_{t=1}^{T}[M(t)]^2}}, \tag{4}$$

where $M(t)$ is a template of the anticipated response. m-VEPs are ideal for immersive and interactive gaming environments, such as virtual reality (VR) or augmented reality (AR) games. The natural and intuitive interaction provided by motion-based stimuli can enhance the realism and engagement of the gaming experience. However, m-VEPs typically have a lower response rate compared to SSVEPs, making them less suitable for games that require rapid input.

Finally, **Chromatic VEPs**—evoked by sudden color changes—also fall under this category. Although they share some properties with TVEPs, their use may be optimized for environments in which color transitions can serve as distinct, easily recognizable cues without the need for high-frequency stimulation [25]. Chromatic VEPs arise from color changes in the visual field, emphasizing neural responses to hue rather than pure luminance transitions, making them suitable for color-based games or tasks that involve visual exploration. By isolating chromatic contrast, these VEPs can be distinguished from standard flicker- or pattern-driven responses [99], [100].

Implementation often requires calibrating monitors so that color changes do not introduce significant luminance artifacts and precise calibration to ensure accurate signal detection [25]. EEG data are then analyzed using either time-locked averaging (to capture transient color-onset responses) or frequency-domain methods (if color alternation is periodic). Classification can employ correlation with a pre-learned chromatic template:

$$\rho_{chromatic} = \frac{C_i(t)\, x(t)^T}{\sqrt{(C_i(t)\, C_i(t)^T)\,(x(t)\, x(t)^T)}}. \tag{5}$$

Due to potential individual differences in colour perception, robust calibration is required.

This grouping is particularly well-suited for games where discrete commands are issued, and the BCI must quickly and reliably detect a single intended action.

3) LOW-FATIGUE, IMMERSIVE OR MULTIMODAL VEPs

Gaming sessions are often long, and user comfort is a critical consideration. Paradigms in this category are designed to minimize visual fatigue while maintaining robust evoked responses, and in some cases, they integrate additional sensory modalities to enhance immersion. **Flickerless VEPs** are developed to induce responses with minimal harsh flickering; instead, they rely on subtle intensity adjustments that yield a steady or quasi-steady-state response without causing eye strain, making them ideal for casual or relaxation-based games [101]. This type of VEP enhances user comfort during extended gaming sessions. Though flickerless VEPs can alleviate user fatigue, they generally exhibit lower amplitude peaks, reducing the SNR. Advanced filtering may be needed to isolate the subtle responses. These systems appeal to users requiring a more comfortable experience over longer durations [101], [102]. **Chromatic VEPs**, by using gradual or moderate color transitions rather than high-contrast brightness changes, further reduce the discomfort associated with prolonged exposure to rapidly flickering stimuli [25], [103]. Finally, **Audio-Visual Evoked Potentials (AVEPs)** emerge from synchronized auditory and visual cues. By engaging multiple sensory modalities, AVEPs can exhibit stronger or more distinctive features than either unimodal VEPs or auditory evoked potentials alone [104]. They are particularly beneficial in VR/AR environments or narrative-driven games, where immersive and synchronized sensory inputs enhance the gaming experience. In practical setups, each target may combine a flicker or motion pattern with a short tone, creating temporally aligned bimodal stimuli. Feature extraction typically proceeds by isolating both the visual (VEP) and auditory (AEP) components, then fusing them into a single classification framework. A probabilistic approach might define:

$$\hat{k} = \arg\max_{k} P(\text{AVEP features} \mid k)P(k), \tag{6}$$

where the prior $P(k)$ is uniform across targets, and the likelihood term depends on the fused sensory features.

The proposed grouping aligns with the diverse requirements of gaming BCIs. High-speed, continuous control VEPs (SSVEP, c-VEP, and f-VEP) enable rapid, ongoing interaction that is essential in fast-paced games, while discrete, action-triggered VEPs (TVEP, PR-VEP, m-VEP, and Chromatic VEP) are ideal for situations where the BCI needs to issue individual commands. Meanwhile, the low-fatigue and multimodal approaches (Flickerless VEP, Chromatic VEP, AVEP) prioritize user comfort and immersion, making them well-suited for long gaming sessions. By categorizing VEPs, developers can select or design stimulus paradigms that best match the specific control requirements, speed, and comfort needed for various gaming scenarios (see Table 3).

D. SIGNAL PROCESSING TECHNIQUES AND GAMING INTERFACE

The signal processing pipeline is a critical component of VEP-based BCIs, enabling the accurate detection and interpretation of neural signals in real-time applications. This section provides a comprehensive overview of the signal processing stages involved in these systems, encompassing preprocessing, feature extraction, classification, and real-time adaptation.

1) PRE-PROCESSING AND ARTIFACT REMOVAL

A major challenge in EEG-based BCI application is the need to eliminate background noise before analysis. This noise can stem from both external and internal sources. External sources include electronic devices such as mobile phones, computers, and lighting fixtures, while internal sources involve factors like body movement, breathing, fluctuations in skin resistance, and other bioelectrical signals, including electromyographic (EMG), electrocardiographic (ECG), and electrooculographic (EOG) activity.

As a result, raw EEG data requires preprocessing for reliable analysis. To accomplish this, various preprocessing techniques can be employed, including [23], [37], [53], [65], [66], [71], [75]:

- Applying notch filtering at 50 or 60 Hz (depending on the region) to eliminate power line interference.
- Using high-pass filtering with a low cut-off frequency to remove baseline drift.
- Implementing band-pass filtering to isolate relevant frequency bands.
- Segmenting continuous EEG data into specific time windows aligned with events (epoching).
- Clipping EEG amplitude to keep signal values within a defined range.
- Discarding poor-quality trial samples from the EEG dataset.
- Standardizing data by normalizing it to a zero mean and unit variance (z-score normalization) to enhance convergence and prevent local minima issues.
- Down-sampling the data to improve computational efficiency and reduce memory usage.
- Selecting relevant electrode positions based on the specific application requirements.
- Removing artifacts using thresholding methods, such as Principal Component Analysis (PCA) or Independent Component Analysis (ICA).

2) FEATURE EXTRACTION

Once the EEG signal has been preprocessed to remove noise, the next important step is to extract its most relevant features. In BCI systems, common feature types include statistical, manually selected, and adaptive data-driven features. Selecting an appropriate method is vital due to the signal's complexity and variability. Features can be extracted from different domains, such as time, frequency, time-frequency, and spatial. However, relying only on temporal features overlooks spectral information, while using only frequency-based features neglects important temporal dynamics.

Two widely used feature extraction techniques are the Discrete Wavelet Transform (DWT) [105] and Wavelet Packet Decomposition (WPD) [106]. These methods enable multiresolution and multiscale decomposition of EEG signals, making them highly effective for capturing essential information across different frequency bands. Additionally, they can extract dynamic features, which is critical given the nonstationary and nonlinear nature of EEG data.

Time-frequency analysis techniques are particularly valuable for EEG processing due to the signal's highly dynamic characteristics. Combining spatial and frequency domain methods can enhance feature distinctiveness, leading to

TABLE 3. Comparison of visual evoked potential (VEP) types in video game applications Note: VEP types in bold are the most commonly used in VEP-based BCI video games.

VEP Type	Stimulus	Response Type	ITR	User Fatigue	Applicable Game Genres	Why Suitable for Games	Implementation Challenges	Ref
SSVEP	Repetitive flicker	Continuous, frequency-specific	High	High	Action, RTS, arcade games	High ITR, continuous control, fast-paced interaction.	Visual fatigue from repetitive flicker stimuli.	[47], [75], [82]–[88]
c-VEP	Code-modulated	Code-correlated	High	Low	Competitive or simulation games	Robust and accurate in dynamic environments.	Requires sophisticated processing hardware and precise calibration.	[31], [89]
m-VEP	Motion-based	Dynamic, parietal response	Low-Medium	Low	VR exploration, rehabilitation games	Natural motion-based interaction, immersive.	Lower ITR and slower response make it less suitable for fast-paced games.	[24], [32], [33]
TVEP	Sudden change	Transient	Medium	Low	Decision-making or point-and-click games	Simple commands with low fatigue.	Limited scalability for complex or high-speed games.	[93]–[95]
Flickerless VEP	Smooth transitions	Comfortable, lower fatigue	Medium	Very Low	Casual, relaxation-based games	Comfortable for prolonged use, suitable for sensitive users.	Limited speed and command scalability reduce suitability for fast-paced games.	[101], [102]
PR-VEP	Pattern reversal	Transient	Low-Medium	Low	Research or diagnostic games	Reliable and precise under controlled conditions.	Low ITR limits its use in interactive or dynamic games.	[96]–[98]
Chromatic VEP	Color changes	Color-sensitive responses	Medium	Low	Color matching or visual exploration games	Engaging gameplay focused on color stimuli.	Requires high-quality displays and precise calibration for accurate responses.	[99], [100]
f-VEP	Frequency changes	Dynamic, robust response	High	Medium	Competitive or high-action games	High-speed dynamic response, supports complex tasks.	Complex signal processing can delay implementation and real-time responsiveness.	[92]
AVEP	Audio-visual stimuli	Multimodal integration	Medium	Medium	VR/AR exploration, story-driven games	Immersive multimodal interaction.	Increased cognitive load for players in high-intensity gaming scenarios.	[104]

improved classification accuracy. Moreover, selecting the most effective electrode positions is crucial for optimal feature extraction. This can be achieved using spatial domain techniques that assign weights to different electrode locations. Since EEG signals typically yield high-dimensional feature sets, statistical transformation methods such as PCA [107] and ICA [108] are often applied for dimensionality reduction. However, these methods can be computationally demanding and may negatively impact classification accuracy.

To address the issue of high dimensionality, evolutionary algorithm (EA) optimization [109] techniques are employed to refine feature selection from large datasets. Another highly influential method in EEG feature extraction is the filter bank approach, particularly the Common Spatial Pattern (CSP) technique [110]. CSP applies spatial filtering to transform brain signals into a space where feature set variation is maximized, while minimizing variation in the remaining data. However, CSP may not always achieve accurate performance due to individual differences in ideal frequency bands. Selecting the most suitable filter band can enhance performance, though pure CSP-based selection can be time-consuming [110]. Various CSP adaptations, such as the Adaptive Composite Common Spatial Pattern (ACCSP) and Self-Adaptive Common Spatial Pattern (SACSP) algorithms [111], have been introduced to improve performance in BCI systems.

An important metric during feature extraction is the signal-to-noise ratio (SNR), which quantifies the clarity of the extracted signal relative to background noise. In the context of frequency-based features, the SNR at a given frequency f_i is often computed by comparing the power $P(f_i)$ at the target frequency with the average power in neighboring frequency bins. This relationship is mathematically represented as:

$$S_i = \frac{P(f_i)}{\frac{1}{2}\left[P(f_i - \delta f) + P(f_i + \delta f)\right]}, \tag{7}$$

where δf represents the frequency offset. A high S_i indicates that the evoked response at f_i is strong relative to the surrounding noise, which is critical for reliable feature extraction.

3) CLASSIFICATION

In the domain of BCIs, the selection of appropriate classification algorithms is crucial for accurate interpretation of neural signals. Traditional supervised methods, such as Support Vector Machines (SVM) [112] and Random Forest (RF) [113], have been widely used for this purpose. However, these methods may overlook important EEG information during the feature extraction process.

To address these limitations, deep learning models capable of directly processing raw EEG data have gained popularity [114]. In applications such as healthcare and gaming, convolutional neural networks (CNNs) [21], [114], [115], [116] and hybrid CNN architectures [117] have played a significant role. These models use spatial and temporal kernels to extract features either across multiple EEG channels simultaneously or from a single channel over different time periods [114], [115]. Some studies have also investigated the combination of CNNs with auto-encoders for EEG classification [118]. Nevertheless, CNNs often struggle to capture long-range dependencies within EEG signals, which can hinder their effectiveness in certain contexts [115].

In contrast, the Transformer architecture, originally developed for natural language processing tasks, offers a novel approach to EEG signal classification. By utilizing multi-head attention mechanisms, as demonstrated in models like BERT [119] and GPT-2 [120], Transformers can capture global dependencies without relying on convolutional or recurrent layers. This capability has enabled their adaptation to diverse tasks, including image classification, video analysis, speech recognition, and music generation [121], [122], [123], [124]. This flexibility makes the Transformer architecture particularly promising for EEG classification, offering greater interpretability compared to other deep learning models [125].

Despite these advantages, Transformers also present challenges. They may unintentionally prioritize noisy EEG segments, and their attention mechanisms are computationally intensive, which could pose difficulties for real-time applications or systems with limited processing power [126].

An additional critical performance metric in BCI systems is the information transfer rate (ITR), which quantifies the speed at which a system can communicate information. The ITR, measured in bits per minute, is defined as:

$$ITR = \left(\log_2 N + P\log_2 P + (1-P)\log_2 \frac{1-P}{N-1}\right) \times \frac{60}{T}, \tag{8}$$

where N is the number of possible targets, P is the classification accuracy (expressed as a fraction), and T is the average time in seconds required to make a selection. This formula combines both the accuracy and the speed of the BCI, making it especially relevant in applications such as gaming, where rapid and accurate command execution is needed.

Deep learning models, such as Transformers, are explored for improving ITR by effectively capturing long-range EEG dependencies. This in turn may lead to faster decision-making and improved overall performance of the BCI system in real-time applications.

4) GAMING INTERFACE

Since 2000, gaming technology has seen remarkable advancements, significantly influencing BCI applications [64], [65]. The development of virtual environments and improvements in 2D and 3D gaming interface design have driven the creation of advanced BCI-based games controlled by various EEG features [30], [127], [128]. A key factor in the success of neurofeedback games is offering an engaging and immersive gaming experience.

The interface can be designed in 2D, 3D, or integrated with virtual reality (VR). Depending on the design and system requirements, the outputs from the control generator are meaningfully translated into game commands [90], [91], [127]. Players receive real-time feedback on their brain activity, either through visual displays on a screen or within the game environment itself. This feedback allows them to learn how to regulate their EEG patterns to optimize their performance and achieve higher game scores.

E. APPLICATIONS AND RESEARCH DIRECTIONS

1) ACCESSIBILITY AND INCLUSIVE GAMING

Integrating VEP-based BCIs into gaming has enhanced both entertainment and accessibility. By enabling users to control game elements through brain signals, these systems not only elevate the gaming experience but also provide alternative interaction modalities for individuals with disabilities. In this section, we explore examples of VEP-based BCI games, discuss inclusive design strategies, and highlight how adaptive control mechanisms foster a more accessible and engaging environment.

Among the most popular VEP-based techniques are SSVEP and m-VEP, which have been successfully implemented in a variety of game applications. For instance, the *Mind Balance Game* [129] uses phase-reversed checkerboards flashing at 17 and 20 Hz to help players maintain a character's balance, achieving an accuracy of 89.5% and a bit rate of 10.3 bits/min. Similarly, the *Car Racing Game*

[66] utilizes two different flicker frequency ranges to allow real-time navigation on a race track, typically achieving stable user responses within 3–6 seconds. In the *Tower Protection Game* [130], a consumer-grade SSVEP-based system utilizing the Emotiv EPOC headset allows players to build defenses by focusing on stimuli flashing at 12.8 Hz, demonstrating the potential for out-of-lab application. The *Spacecraft Game* [65] is designed specifically for clinical applications; players steer a spacecraft by focusing on directional cues generated at a comfortable 3–5 Hz, while a single-electrode recording from the occipital area (Oz) captures the relevant SSVEP responses. Additional examples include the *Virtual Claw Game* [131], which achieved an average accuracy of 96% and an ITR of 18.23 bits/min, and the *Checker Game* [64], where BCI-driven control of a robotic arm is optimized through adjustments of various game parameters.

Hybrid games combining BCI input with traditional controls—such as keyboards for movement and brain signals for shooting actions—have also been developed. Research indicates that such hybrid systems tend to offer superior accuracy compared to fully BCI-controlled games [132]. Moreover, these novel approaches enhance accessibility in gaming; studies suggest that 2% of disabled individuals cannot play video games at all and 9% face limitations. BCIs could significantly address these challenges by offering alternative interaction methods [132]. Table 5 summarizes several notable examples of VEP-based BCI games, highlighting their design features and performance outcomes.

Inclusive game design for users with disabilities relies on several key principles. Game designers are increasingly incorporating customizable control schemes, adjustable difficulty levels, and alternative input modalities, such as gaze-based interfaces, to accommodate users with diverse motor and cognitive abilities [133], [134]. By integrating these accessibility features, developers create interfaces that not only engage players with disabilities but also promote rehabilitation and cognitive enhancement through interactive gameplay [48], [135].

VEP-based BCIs also support adaptive gameplay and social engagement. Their non-invasive, intuitive nature allows for real-time adjustments in game difficulty and pace based on the user's cognitive load and attention [50]. Moreover, these systems support multiplayer experiences by enabling direct neural communication, fostering cooperative play and emotional connectivity among users [45], [47]. By capturing and translating VEPs into gameplay commands, developers can create immersive environments that overcome traditional control barriers, ensuring that a diverse range of players can enjoy a seamless and socially engaging gaming experience.

In summary, VEP-based BCIs not only enhance entertainment by enabling novel, responsive gameplay but also empower a broader audience through inclusive design and adaptive control strategies. This convergence of technology and design creates a more accessible, fair, and engaging gaming environment for all.

2) ADAPTIVE DIFFICULTY AND PERSONALIZED GAMING EXPERIENCES

Researchers are increasingly investigating neuroadaptive gaming systems that dynamically adjust game parameters according to users' neural responses using VEP-based BCIs. Continuous monitoring of VEP signals allow these systems to adjust difficulty levels, environmental stimuli, and narrative progression in real-time, optimizing the gaming experience according to the user's cognitive state [50]. For instance, work by Arslan and Filiz [48] demonstrated how EEG-based BCIs can monitor player engagement and adjust game difficulty on the fly, creating more personalized and engaging experiences. Using machine learning algorithms and real-time signal processing, these neuroadaptive systems decode neural activity to predict cognitive states during gameplay, enabling a seamless evolution of the gaming environment in response to changes in cognitive load, engagement levels, and emotional states, ultimately enhancing immersion, enjoyment, and overall player satisfaction [50].

In parallel, significant efforts are underway to evaluate the user experience of VEP-based BCI games. Researchers conduct both qualitative and quantitative studies to assess the effectiveness, usability, and overall user perception of these systems. Utilizing user-centered design and iterative usability testing, these studies aim to refine BCI game interfaces and interactions [47]. Insights from this research have led to the development of accessible, intuitive, and engaging interfaces, fostering a more inclusive gaming environment. For a comprehensive overview of recent studies on VEP-based BCI gaming systems—including modalities, applications, performance metrics, and challenges—see Table 4.

Overall, the field of BCI gaming applications encompasses a range of challenging projects aimed at enhancing the technology's functionality, delivering an innovative user experience, and improving cognitive functions. Advancements in research methodologies and interdisciplinary collaborations are refining VEP-based BCIs, leading to improved gaming experiences, neuroscience developments, and more effective human-computer interactions.

3) NEUROREHABILITATION AND THERAPEUTIC GAMING

VEP-based BCIs have emerged as promising tools in the field of neurorehabilitation, offering novel approaches to both therapeutic intervention and cognitive enhancement through engaging gaming environments. By integrating neurofeedback with video game mechanics, these systems provide non-invasive, real-time feedback on neural activity, enabling targeted training that can improve attention, inhibitory control, and working memory in clinical populations. The following subsections discuss two significant applications: therapeutic interventions for Attention Deficit

TABLE 4. Summary of VEP-based BCI Studies, HS = healthy subjects, TS = trials per session.

Ref.	Modality	Application	Data Set	Game Name	Model	Performance & Challenges
[136]	SSVEP	Consumer-grade SSVEP detection at high-frequency	Private, 15HS, 40TS	Not Given	Common Spatial Filtering, Canonical Correlation, Logistic Regression	Accuracy: 80% (17-25Hz), 67% (31-40Hz). Challenges: weaker responses at higher frequencies, user variability, balance between fatigue and detection
[82]	SSVEP	3-class BCI for gaming	Private, 5HS	Not Given	LDA, SVM, RVM with CSP	Accuracy: 85-90% (SVM), 78% (LDA). Challenges: inter-individual variation, noise sensitivity
[137]	SSVEP, MI, ERN, RSVP	BCI gaming impact on brain state	Private, 14HS	BCI Gem Game	MVAR Model	Changes in fronto-central networks. Challenges: EEG electrode limits, short resting data
[30]	SSVEP	BCI Gaming	Private, 6HS	Unity3D Private Game	CCA	Challenges: EEG noise, latency, low transfer rate, calibration, attention demand, limited controls
[138]	Blink Detection	Simple game control	Private, 10HS	BlimkFruity Game	BrainFlow library	86% accuracy for gameplay. Challenges: limited engagement due to single-level design
[89]	cVEP	BCI for gaming	Private, 10HS	Connect 4 Game, Unity & Meduza	Canonical Correlation Analysis	74% selection accuracy. Challenges: signal quality, calibration, attention needs
[139]	SSVEP	BCI gaming for stroke rehabilitation	Private, 15HS	Short video clips of picking up a ball with the left and right hands.	CSF and ANOVA	Higher mu suppression in BCI-AO. Challenges: signal quality, engagement
[140]	SSVEP	BCI for children with disabilities	Game Jam participants	Many Games.	Signal processing, classification	75% engagement in children with neurological disabilities. Challenges: SSVEP variability, consistent signal quality
[141]	EEG	Game for ADHD concentration	10HS	Cog-Maze Brain-Computer Game	EEGlab Toolbox	32.8% attention improvement. Challenges: small sample, lab conditions
[142]	EEG Alpha/Beta	Game experience evaluation	20HS	DX-Ball Game	-	Classifies attention states. Challenge: single game, limited sample size
[85]	SSVEP	BCI gaming	12HS	Kessel Run Game	CCA in MATLAB, PSD Analysis	Avg. 55% accuracy, max 79%. Challenges: signal quality, user variability
[127]	EEG	ADHD diagnosis via BCI game	5HS, 4ADHD	FOCUS Game, Unity3D (Serious Game)	SVM	Accurate ADHD detection. Challenges: signal noise, subject variation
[143]	EEG	BCI gaming with action observation	Private, 15HS	Two AO Games: 1) flickering action video -miner who mines gold; 2) movement of action video - a farmer lifting his arm.	OpenVIBE software classification	Value added with character movement observation. Challenges: signal quality, engagement
[64]	SSVEP	BCI gaming	2HS	LED checkerboard and robot arm	FFT	Accuracy: 91-95%. Challenges: calibration time, electrode comfort
[144]	EEG	Cognitive training via neurofeedback game	Private, 5HS	Neurofeedback Game	Entropy estimation	Improved attention and memory. Challenges: real-time processing, EEG variability
[128]	EEG	Engagement in VR driving for ASD	16 ASD males	VR-based driving system	Multiple classifiers	Classification accuracy 75-85%. Challenges: limited features
[145]	EEG	Stress detection in gaming	Private, 10HS	Word search game	CNN, RNN, Autoencoders	3-level stress detection at 77.2% accuracy
[75]	SSVEP, RSVP	SSVEP-RSVP hybrid for gaming	14HS	Not Given	CSP, HMM	AUC 0.812. Challenges: target overlap, attention fatigue
[146]	EEG	BCI based Virtual Robotic Manipulator Control	12HS	Not Given	ICA, LDA, HMM	High error in multi-state tasks. Challenges: session variability, user adaptation
[83]	SSVEP	6-DOF robotic arm control	5HS	Not Given	CSP, LDA	Low precision for some (40% < 50%). Challenges: dry electrodes, user variability

Hyperactivity Disorder (ADHD) and broader cognitive rehabilitation strategies.

ADHD is a prevalent neurodevelopmental disorder characterized primarily by inattention, hyperactivity, and impulsivity [147]. Affecting approximately 5% of children globally, ADHD significantly impacts academic performance, social interactions, and overall quality of life [148]. Current standard treatments primarily involve pharmacological agents and behavioral therapies. Although stimulant medications demonstrate efficacy, adverse effects such as headaches, sleep disturbances, and decreased appetite frequently occur [149]. Behavioral interventions, on the other hand, require sustained commitment and may deliver gradual improvements, underscoring the need for alternative or complementary therapeutic methods.

In response to these limitations, neurofeedback delivered through BCIs emerges as a novel approach for addressing attentional deficits in ADHD populations [65], [147]. Neurofeedback involves providing real-time feedback on brain activity, allowing individuals to modulate their neural patterns consciously. By integrating neurofeedback into engaging activities like video games, BCIs can enhance motivation and compliance among children [53], [65], [150]. Children are naturally drawn to games, particularly well-designed ones. Research indicates that games incorporating subtle exercises can effectively aid children in improving concentration, self-control, and memory [151], [152]. This approach has also proven beneficial for children with ADHD, where simple 2D games designed to enhance inhibitory control and working memory have shown promising results [153]. VEP-based BCIs are particularly suitable due to their non-invasive nature and ability to provide immediate feedback based on visual stimuli.

One method for assessing attention levels in BCI applications is the beta-to-alpha power ratio obtained from EEG signals. A higher ratio indicates increased attention, while a lower ratio suggests reduced focus [154], [155]. The formula for calculating the arousal index A is:

$$A = \frac{E_\beta}{E_\alpha}, \tag{9}$$

where E_β is the mean beta power, and E_α is the mean alpha power.

Expanding upon this approach, research by Kim et al. [25] examined color vision anomalies in children with ADHD using VEP methodologies. Their study demonstrated that children with ADHD exhibited distinctive alterations in VEP parameters—specifically amplitude and latency—compared to neurotypical controls. These findings suggest that abnormalities in color processing may serve as neurophysiological markers of attentional impairments, highlighting the potential for optimizing visual stimuli parameters, such as color attributes, to enhance the efficacy of VEP-based neurofeedback systems in attention-focused therapies.

In recent developments, innovative studies have integrated VEP-based BCIs within immersive gaming frameworks specifically targeting ADHD rehabilitation. For instance, Arpaia et al. [156] developed an Augmented Reality (AR)-based, single-channel SSVEP BCI designed for robotic control within ADHD therapeutic contexts. Utilizing AR smart glasses, their system required participants to direct visual attention towards flickering stimuli, effectively controlling robotic devices. Despite utilizing only a single EEG channel, their findings provided preliminary yet promising evidence for feasibility and therapeutic value, with wearable AR technologies enhancing patient engagement and adherence.

Complementing these experimental findings, a comprehensive review by Sagiadinou and Plerou [157] analyzed existing BCI-based neurofeedback protocols for ADHD rehabilitation. They discussed extensively how SSVEP and P300 paradigms could enable improvements in attentional control through adaptive and individualized training programs. Their review emphasized the need for personalized calibration and adaptive algorithmic approaches tailored to the unique neural profiles of individuals, reinforcing the suitability of VEP-based BCIs for cognitive rehabilitation through serious gaming.

Further illustrating practical implementation, the "Spacecraft Game" [65] exemplifies an SSVEP-based therapeutic gaming application. Participants maneuver a spacecraft, avoiding obstacles and aiming for specific targets, guided initially by static and subsequently flickering directional arrows. With stimulation frequencies ranging between 3–5 Hz to ensure comfort, this game is particularly tailored for children with attention deficits. Employing a simplified EEG configuration—using a single occipital electrode (Oz)—this system prioritizes ease-of-use and patient comfort while effectively capturing relevant neural responses, thereby achieving an optimal balance between simplicity and therapeutic functionality.

Beyond the direct treatment of disorders such as ADHD, VEP-based BCIs are increasingly explored for broader cognitive rehabilitation applications. Specifically, cognitive enhancement games utilize neurofeedback techniques to promote neuroplasticity by engaging users in repetitive, goal-directed tasks targeting specific neural pathways. These games typically aim to improve cognitive functions such as attention, memory, and executive processes. Continuous feedback mechanisms integrated within these games encourage the development of compensatory neural strategies, facilitating sustained improvements in cognitive performance [48].

Additionally, the application of VEP-based BCIs within neurotherapeutic gaming contexts has garnered significant interest, particularly for motor recovery and cognitive rehabilitation. Interactive, game-based therapeutic tasks delivered through these BCIs enhance patient motivation and compliance. Empirical studies indicate that neurogaming environments incorporating m-VEP and SSVEP paradigms

TABLE 5. Examples of SSVEP-Based BCI Games for inclusive and therapeutic entertainment.

Game	Description	Results
Mind Balance [129]	An SSVEP-based game where players balance a character on a tightrope by focusing on phase-reversed checkerboards (17 Hz and 20 Hz) flanking the avatar. A subject-specific model, calibrated with 15-s focus periods, detects attention in real time to prevent the avatar from falling.	Six participants achieved 89.5% average accuracy and 10.3 bits/min, demonstrating reliable control.
Car Racing [66]	An SSVEP-based game for navigating a car on a track using four checkerboards (UP, DOWN, LEFT, RIGHT) at low (5–8 Hz) or medium (12–17 Hz) frequencies. EEG data from six electrodes (e.g., Pz, POz) at 256 Hz drives an adaptive BCI system.	Responses stabilized within 3–6 s. Low-frequency range (5–8 Hz) outperformed medium range in controllability and speed.
Tower Protection [130]	An SSVEP-based tower-defense game using Emotiv EPOC EEG hardware. Players focus on 12.8 Hz stimuli to build defenses, with EEG signals filtered (2–45 Hz) and processed via ICA for SSVEP detection.	Twenty-five participants validated its feasibility outside labs, suggesting potential for public demonstrations.
Spacecraft [65]	An SSVEP-based game where players steer a spacecraft past obstacles by focusing on 3–5 Hz directional arrows. Designed for clinical use, it uses single-electrode (Oz) EEG for comfort.	Tailored as a neurotherapy tool for children with attention-deficit disorders, enhancing selective attention.
Virtual Claw [131]	An SSVEP-based virtual claw machine controlled via 15 Hz (movement) and 17 Hz (drop/clamp) stimuli. EEG from the Oz channel tracks peak power to detect focus, tested with three volunteers.	Achieved 96% accuracy and 18.23 bits/min ITR. BCI accuracy correlated with attention, suggesting therapeutic potential.
Checker [64]	An SSVEP-based game where players focus on flickering LED-lit checkerboard squares to trigger commands for a robotic arm.	Analyzed two-player mode and gameplay parameters (e.g., stimulus distance, occlusion), proposing optimization strategies.

effectively stimulate neuroplasticity, thus aiding the recovery of individuals with various neurological conditions [158]. The inherent flexibility of these technologies allows tailored training sessions, which optimize therapeutic efficacy through individualized real-time feedback.

Moreover, the use of VEP-based BCI gaming in cognitive rehabilitation for individuals with neurodegenerative disorders, such as dementia and Alzheimer's disease, has demonstrated notable efficacy. For instance, EEG-based serious games that dynamically adjust difficulty based on real-time neural activity have been successfully employed to enhance cognitive functions, as reported by Ata et al. [159]. Through repetitive tasks designed to reinforce neural pathways, these gaming interventions not only provide engaging activities for patients but also significantly enhance memory and cognitive agility. Similarly, Beveridge et al. [32] found that m-VEP-based neurogaming consistently delivered reliable outcomes across diverse age groups, thereby establishing its utility for elderly populations at risk of cognitive decline, as well as younger patients experiencing cognitive deficits.

Further extending the therapeutic scope, VEP-based gaming applications also show considerable promise in motor rehabilitation. Neurofeedback-driven games using VR have been utilized effectively to restore motor function in individuals recovering from spinal cord injuries or stroke. Research indicates that immersive VR environments combined with VEP-based BCIs significantly enhance rehabilitation outcomes by actively engaging users' brain functions [32]. Due to their sensitivity in detecting subtle neural signals, VEP-based BCIs are particularly suitable for rehabilitation programs targeting patients with severe motor limitations.

However, despite these promising outcomes, the effectiveness of VEP-based neurogaming interventions critically depends on the quality of EEG data acquisition. High-density EEG configurations, while offering superior spatial resolution and enhanced accuracy in detecting neural responses, often increase patient discomfort and require longer setup times [158]. Consequently, a careful balance between signal quality and user comfort is essential, especially for sustained therapeutic applications. To further optimize clinical efficacy and user experience in BCI-based neurotherapy, future research should focus on refining the balance between electrode density and practical usability.

In these neurofeedback systems, monitoring EEG biomarkers—such as the beta-to-alpha power ratio—is commonly employed as an objective measure of attentional states. Integrating these quantitative metrics enables dynamic adjustment of game difficulty and personalized training protocols. Repetitive practice enabled by adaptive gaming environments, coupled with immediate neurofeedback, reinforces neural activity patterns, potentially accelerating recovery and broadly enhancing cognitive function.

In summary, VEP-based BCIs represent a highly promising avenue for advancing neurorehabilitation and therapeutic gaming. By integrating engaging gameplay with real-time neurofeedback, these systems offer a non-invasive approach to cognitive enhancement and introduce advanced therapeutic strategies that complement traditional treatments for disorders such as ADHD.

4) MULTIPLAYER AND SOCIAL INTERACTION APPLICATIONS

VEP-based BCIs have paved the way for advanced multiplayer gaming experiences and advanced emotion detection techniques. For example, Bonnet et al. [160] demonstrated the potential for collaborative gameplay by designing a multi-user BCI video game based on motor imagery, which opens up new possibilities for social interaction in virtual environments. Similarly, Diya et al. [142] applied BCI technology to evaluate user experience, revealing that these systems can effectively detect and analyze gamers' emotions, thereby enriching the multiplayer experience.

In addition to enhancing social interactions, VEP-based BCIs are also instrumental in improving task efficiency during gameplay. Research by Filiz and Arslan [30] on a SSVEP-based BCI for video games provided valuable insights into system response times. Their findings indicated that while the average task took 8.57 seconds to complete, the best-case scenario required only 1.4 seconds to capture a bait in the game. Such results underscore the critical importance of optimizing BCIs for scenarios demanding rapid responses, ensuring that both the efficiency and enjoyment of gameplay are maximized.

III. CHALLENGES AND LIMITATIONS

Although VEP-based BCIs demonstrate considerable potential in gaming applications, significant technological and usability challenges currently restrict their widespread adoption. This chapter outlines critical limitations, including technical constraints, user adaptability concerns, and associated risks. Furthermore, it identifies directions for future research aimed at addressing these barriers to enhance system reliability, user comfort, and overall performance.

A. TECHNOLOGICAL AND PERFORMANCE CONSTRAINTS

VEP-based BCIs face several technological challenges, particularly issues related to signal-to-noise ratio (SNR). Although VEPs benefit from their time-locked nature—which inherently improves their SNR through signal averaging—background EEG noise, artifacts, and inter-individual variability can complicate reliable extraction of the relevant signal without advanced signal processing techniques or high-resolution EEG systems. Additional constraints include calibration requirements and computational demands. High-resolution EEG setups, while necessary for effective classification of VEP responses, pose challenges related to accessibility and affordability. Furthermore, real-time performance optimization remains critical, as minimizing latency while maintaining high classification accuracy is essential for providing an effective and responsive gaming experience.

SSVEP-based BCIs, in particular, require flickering stimuli for control, which can lead to visual discomfort and fatigue. There is also the risk of triggering photosensitive epilepsy in some users. To mitigate these effects, developers must explore alternative stimulus presentation methods, such as adaptive frequency alteration, that balance usability with comfort [161].

B. USER ADAPTABILITY AND LEARNING CURVE

A major challenge in VEP-based BCIs is user adaptability. Many users require extended training periods to generate consistent VEP responses, affecting accessibility and ease of use. Unlike traditional gaming controls, BCIs demand continuous cognitive effort, which may lead to mental fatigue over time. Additionally, variability in neural responses across individuals requires personalized calibration strategies.

To address these issues, future research should focus on adaptive algorithms that dynamically modify system parameters based on real-time feedback. Hybrid BCIs that integrate additional physiological signals, such as motor imagery or eye tracking, could enhance user control and expand interaction possibilities. Furthermore, reinforcement learning techniques could be applied to gradually adjust classifier parameters in response to user performance, improving long-term usability.

IV. FUTURE RESEARCH AND EMERGING TRENDS

Current developments in machine learning and neuroadaptive gaming offer promising directions for VEP-based BCIs. Integrating BCIs with augmented reality (AR) and mixed reality (MR) could lead to more immersive experiences [45]. By incorporating brain-controlled interactions into AR/MR environments, users could engage with digital content in new and interactive ways, enhancing engagement and accessibility.

Emotion recognition and affective computing are also promising areas for VEP-based gaming. By combining VEP responses with other physiological signals, such as heart rate variability and electrodermal activity, systems could adapt gameplay in real time based on player emotions [135]. This approach could enhance game personalization and improve user experience in both entertainment and therapeutic applications. Portable BCI gaming devices with embedded processors may soon enable real-time, wireless gameplay without dependence on external computing resources.

Multiplayer gaming is another area that could benefit from VEP-based BCIs. Research by Ho et al. [87] has demonstrated the feasibility of using SSVEP-based BCIs for multi-agent control, allowing users to collaborate and interact in shared environments through neural signals. Future BCI-enabled multiplayer games could enable brain-controlled team coordination, enhancing cooperation and strategy in gaming.

Despite these advancements, ethical considerations must be addressed to ensure responsible deployment. Privacy, data security, and the potential for cognitive manipulation are key concerns that require regulatory frameworks [162]. Inclusive design principles should also be incorporated to ensure that BCI gaming systems remain accessible to a diverse range of users, including those with disabilities.

Overall, addressing these challenges while using emerging technologies will be essential for the continued development of VEP-based BCIs in gaming. By refining control mechanisms, improving adaptability, and integrating advanced computational techniques, future BCI systems can provide more immersive, efficient, and accessible gaming experiences.

V. DISCUSSION

This systematic review demonstrates that VEP-based BCIs significantly enhance the gaming experience by enabling direct brain control of digital environments. Studies such as [82] and [136] show that VEP responses to visual stimuli offer reliable and fast control, outperforming or complementing traditional input methods in terms of accessibility and engagement. This is particularly valuable for users with physical disabilities, aligning with inclusive system design goals observed in works like [53]. However, performance outcomes vary significantly across studies—from 55% accuracy in [85] to 95% in [64]—often due to differences in stimulus design, user training, and EEG hardware configurations. This variability underscores the need for standardized protocols and evaluation frameworks.

Beyond entertainment, VEP-based BCIs have shown promise in cognitive training and neurorehabilitation. Studies such as [139] and [141] indicate improved attention, working memory, and motor recovery when VEP feedback is integrated into serious games. These findings are consistent with broader neurofeedback research [144], which supports the potential for real-time brain state monitoring to dynamically adapt gameplay and provide therapeutic outcomes. However, while this dual utility is compelling, its broader efficacy remains underexplored, particularly across diverse user populations and long-term use scenarios.

Technical advances in signal processing and machine learning continue to drive progress in this field. Recent approaches, such as those found in [31] and [127], have improved classification performance while reducing the calibration time required for new users. Lightweight neural networks, adaptive filters, and user-specific templates have contributed to better real-time responsiveness. Furthermore, hybrid BCIs that combine VEP signals with eye tracking, EMG, or haptic feedback [75] present promising directions for improving control flexibility and reducing fatigue. These multimodal systems offer the potential to tailor interfaces to individual users and gameplay contexts.

However, several persistent challenges continue to limit reliability and user experience. VEP responses can vary significantly across individuals and recording sessions, making robust generalization difficult. Studies such as [30] report issues with user fatigue, inconsistent engagement, and difficulty sustaining attention to visual stimuli over extended periods. Moreover, ethical concerns surrounding data privacy, consent transparency, and algorithmic fairness have become increasingly relevant as BCIs approach commercial deployment [83].

These limitations constrain the generalizability of current findings. Most studies rely on small samples—typically 5 to 15 healthy adult participants—tested in controlled laboratory environments. This not only restricts statistical power but also fails to account for the variability found in real-world settings. Notably, users with visual impairments or neurodevelopmental conditions are often excluded, despite being core beneficiaries of accessible gaming technologies. In addition, few studies offer direct comparisons between VEP-based systems and other EEG-based paradigms, such as motor imagery or P300, leaving the relative strengths of VEP paradigms insufficiently explored.

Looking ahead, future research must prioritize larger and more diverse user samples, including individuals with varying cognitive and sensory profiles, and test BCI systems in real-world gaming contexts. Longitudinal studies are especially needed to examine adaptation over time, changes in engagement, and any cognitive or behavioral effects of sustained use. Integrating BCI systems with multimodal feedback technologies—such as haptic cues, adaptive audio, or AR/VR—may help reduce fatigue while enhancing immersion and control precision, as suggested in [143].

As BCI research becomes more integrated into interactive technologies and user-centric gaming design, the question is no longer whether VEP-based BCIs can enhance gameplay, but rather how they should be implemented to maximize performance, comfort, and inclusivity while mitigating current limitations. For researchers, designers, and developers aiming to translate VEP-based BCIs into practical gaming systems, several critical considerations must be addressed:

1) How can stimulus design optimize information transfer while reducing fatigue and cognitive load during gameplay?
2) What adaptive methods can address user variability without compromising real-time performance?
3) How can hybrid systems enhance flexibility, precision, and accessibility in BCI interaction?
4) What is the balance between computational cost and real-time performance in consumer-grade EEG systems?
5) How can VEP-based BCIs be made more accessible to users with physical, visual, or cognitive impairments?

Answering these questions is essential to advancing VEP-based BCIs from experimental prototypes to scalable, inclusive gaming systems.

VI. CONCLUSION

This review has explored the role of VEP-based BCIs in gaming, highlighting their ability to enable direct neural interaction through non-invasive, high-speed signal decoding. By analyzing diverse VEP paradigms, signal processing strategies, and interaction models, the review outlines how these systems support both entertainment and therapeutic applications.

While advances in calibration methods, hybrid input designs, and adaptive algorithms are accelerating usability, challenges remain — particularly in addressing user variability, visual fatigue, and ethical concerns related to data use and accessibility. Most current systems still rely on controlled experimental setups and limited participant groups, leaving gaps in ecological validity and inclusivity.

Future research should focus on developing scalable solutions that serve a wide range of users in real-world settings while also improving system robustness, reducing user burden, and ensuring ethical deployment. With ongoing progress, VEP-based BCIs have the potential to reshape interactive gaming into a more inclusive, adaptive, and cognitively engaging experience.

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