

BCI Technology Based on EEG Signals: Principles, Applications, and Future Challenges

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Abstract. Electroencephalography (EEG)-based brain-computer interface (BCI) technology has garnered significant attention in recent years due to its broad potential across multiple domains, including neuroscience research, medical diagnostics, and assistive communication devices. This paper presents a comprehensive review of the fundamental principles underlying EEG-BCI systems, their diverse applications, and the prevailing challenges that impede widespread adoption. It examines key signal processing techniques employed to interpret neural signals, surveys available hardware and software platforms, and highlights clinical implementations such as epilepsy detection, motor rehabilitation, and cognitive state monitoring. Despite considerable advancements, several issues remain unresolved, including the inherent low signal-to-noise ratio of EEG signals, significant individual variability among users, and constraints related to real-time processing and system adaptability. Looking forward, future research directions emphasize the integration of artificial intelligence and machine learning for improved signal classification, enhancing the interpretability and robustness of models, and advancing the development of low-cost, portable, and user-friendly systems. This study aims to provide a thorough overview of the current state of EEG-BCI technology and to facilitate its translation from experimental laboratory settings to practical, real-world applications.

Keywords: EEG, BCI, Signal Processing, Epilepsy Detection, Clinical Applications

1. Introduction

The human brain is one of the most complex systems in nature, and EEG signals are like a window that allows us to glimpse its mysterious electrical activities. As a direct reflection of neural electrical activity in the brain, EEG signals have significant social value in fields such as neuroscience, medical diagnosis, and brain-computer interfaces. In neuroscientific research, EEG provides non-invasive means to explore cognitive functions and mechanisms of brain diseases, advancing human understanding of the brain's mysteries. In the medical field, EEG is the gold standard for diagnosing and monitoring epilepsy, capable of capturing abnormal discharges and assisting in locating lesions. It also plays a crucial role in early screening for diseases such as Alzheimer's disease and sleep disorders. For paralyzed or motor-impaired patients, EEG-based BCI technology significantly improves quality of life, achieving breakthroughs in 'mind control' and providing a technological bridge for disabled individuals to integrate into society. However, the weakness of EEG signals,

their susceptibility to noise interference, and significant individual differences remain key challenges hindering their widespread application. How to extract reliable neural features in high-noise backgrounds? How to make algorithms adapt to different users' 'brain fingerprints'? How to achieve efficient real-time signal decoding? These questions urgently require more advanced signal processing methods to solve.

The in-depth development and widespread application of EEG technology increasingly rely on large-scale, high-quality data resources. In recent years, with the popularization of open science concepts, the open access to resting-state EEG data has become a key driving force for advancing brain research. High-density resting-state EEG, due to its ability to provide superior spatial resolution, has shown great potential in revealing brain network mechanisms and identifying biomarkers for neuropsychiatric diseases. However, existing open datasets still exhibit significant imbalances in geographical distribution and population coverage, predominantly focusing on healthy young populations in Europe and America. This to some extent limits the generalizability and inclusivity of research conclusions and technologies. Against this backdrop, how to utilize and develop existing signal processing and decoding technologies to extract more reliable and robust neural features from these valuable open data has become a core issue facing numerous fields, including BCIs [1].

This paper first analyzes the characteristics and principles of EEG and BCI, then explores various analysis schemes for patients' EEG signals proposed by some scholars to achieve the objectives of this paper. Some research findings not only promote the theoretical development of EEG technology but also provide more reliable and accessible solutions for medical diagnosis and assistive devices. EEG is a non-invasive technique that records brain neural electrical activity through scalp electrodes, widely used in neuroscience research, epilepsy diagnosis, sleep monitoring, and cognitive function assessment, reflecting changes in brain rhythms under different cognitive states and pathological conditions. BCI is a human-machine interaction technology that decodes EEG and other neural signals to enable direct communication between the brain and external devices, providing assistive functions such as thought-controlled wheelchairs or robotic arms for patients with motor dysfunction in medical rehabilitation, significantly improving their quality of life.

2. The Introduction of EEG and BCI

2.1. Definition, characteristics, and principles of EEG signals

EEG is an important neuroimaging technique that non-invasively records the electrophysiological activity of groups of neurons in the brain through scalp electrodes. This method detects synchronous discharges of post-synaptic potentials of pyramidal neurons in the cerebral cortex, capturing biological electrical signals that reflect activities such as thinking, perception, emotion, and behavior. EEG has millisecond-level temporal resolution, allowing real-time monitoring of cortical dynamic activities. However, its spatial resolution is relatively limited due to the need for signals to penetrate through skull tissues.

Characteristic oscillatory rhythms of EEG signals (such as alpha waves: 8-13 Hz, beta waves: 13-30 Hz) exhibit specific modulation under different cognitive states and pathological conditions, making it widely used in the auxiliary diagnosis of motor neuron diseases, Parkinson's disease, and spasticity. However, the microvolt-level signal strength results in low signal-to-noise ratio and highly nonlinear characteristics, making it susceptible to interference from biological artifacts (eye movements/electromyography) and individual differences, which poses significant challenges for signal analysis and identification [2]. Alpha waves and beta waves is shown in Figure 1.

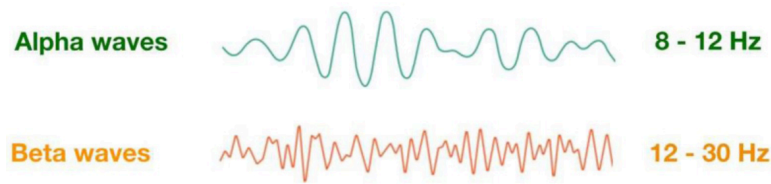


Figure 1. Alpha waves and beta waves [2]

Convolutional neural networks, as a major breakthrough in the field of deep learning, can effectively process highly nonlinear and noisy data, automatically learn the distribution characteristics of EEG data, and achieve precise classification. Compared to traditional methods, this technology demonstrates significant advantages in handling complex EEG signals. Current technological advancements continue to enhance the diagnostic sensitivity of EEG in applications such as epilepsy monitoring, cognitive assessment, and brain-computer interfaces. However, core challenges such as spatial localization accuracy, signal-to-noise ratio optimization, and artifact suppression still need to be addressed through advanced signal processing procedures to ensure the reliability of the analysis results.

2.2. The definition, characteristics, and principles of BCI

A BCI is an interaction technology that establishes a direct communication channel between the brain and external devices by collecting, decoding, and providing feedback on neural signals, opening up new avenues for understanding and expanding mental potential. BCI is a novel human-machine interaction technology that enables direct communication between the brain and external devices by decoding central nervous system electrical activity signals. This system establishes a direct information pathway between the brain and computers or other electronic devices by collecting, analyzing, and converting neural electrical activities such as brainwave signals, without relying on conventional peripheral nerves and muscle tissues. The core of the BCI system lies in real-time decoding of brain intentions and converting them into executable control commands. Its typical architecture includes three key modules: the signal acquisition module, which obtains neural electrical activities through scalp electrodes; the signal processing module, which uses time-frequency analysis, machine learning, and other methods to extract and classify features; and the execution output module, which converts the decoded results into device control commands. Currently, BCI systems based on EEG have shown significant application value in the medical rehabilitation field, such as providing auxiliary communication and environmental control capabilities for patients with motor function disorders. However, the system still faces challenges such as unstable signal quality and significant individual differences, prompting researchers to continuously explore new decoding algorithms and more efficient interaction paradigms. In the future, with the deep integration of neuroscience and artificial intelligence technologies, BCI is expected to achieve broader applications in various fields such as medicine, military, and entertainment [3]. The workflow of a BCI system is shown in Figure 2.

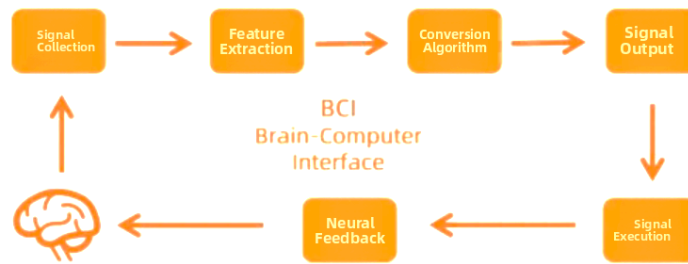


Figure 2. The workflow of a BCI system [3]

In recent years, to enhance the practicality and user experience of BCI systems, researchers have begun to focus on the application of dynamic stopping strategies in ERP-based spelling systems. Mao et al. proposed a dynamic stopping mechanism based on classification confidence, which adaptively terminates the stimulus sequence by setting a probability threshold, significantly improving spelling efficiency. The study used the SWLDA classifier to analyze EEG data from 23 participants under the Row-Column paradigm. The results showed that appropriately selecting the stopping threshold could significantly increase the information transfer rate (ITR) and BCI utility without reducing accuracy. Additionally, researchers categorized participants into three groups based on their performance at different thresholds, further emphasizing the importance of individual calibration in BCI systems [3]. This work provides important references for the optimization of real-time BCI systems, especially in reducing user fatigue and improving interaction efficiency.

2.3. EEG and BCI system's software and hardware development platform

The acquisition, processing, and decoding of EEG signals rely on the support of software and hardware platforms. A complete EEG-BCI system, with its basic structure shown in Figure 3.

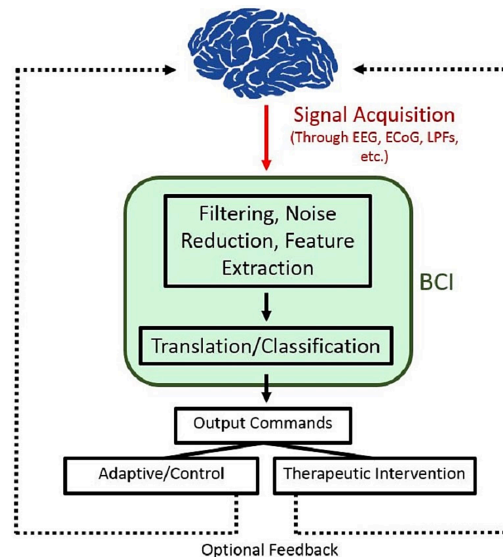


Figure 3. Complete EEG-BCI system [4]

Typically includes signal acquisition hardware, stimulus presentation software, and a signal processing and decoding platform. In recent years, the rapid development of these platforms has

significantly lowered the research threshold for BCI, driving it from laboratory settings to practical applications.

2.3.1. Signal acquisition hardware platform

Signal acquisition is the foundation of BCI systems, with its core being the high-fidelity capture of weak scalp EEG signals. The acquisition platform mainly includes electrodes, analog amplification circuits, analog-to-digital converters (ADC), and front-end processors.

The electrode is the first step in signal acquisition, directly affecting signal quality and user experience. Currently, they mainly fall into three categories. The first type is wet electrodes (such as Ag/AgCl electrodes), which require conductive gel, have high signal-to-noise ratios, and are considered the 'gold standard' in current research and clinical settings. However, their preparation process is cumbersome, the conductive gel tends to dry out, making them unsuitable for long-term use. The second type is semi-dry electrodes, which use a small amount of conductive liquid to reduce impedance, achieving a good balance between signal quality and preparation time. However, the stability of conductive liquid release remains a challenge. The third type is dry electrodes (including microneedle, finger-like, and capacitive electrodes), which do not require conductive gel, are easy to wear, and are very suitable for wearable BCI applications. However, their high contact impedance with the scalp can introduce noise, often requiring high input impedance active electrode technology to ensure signal quality [4].

2.3.2. Stimulus presentation and signal processing software platform

The stimulus presentation software is responsible for generating visual, auditory, or tactile stimuli required for BCI paradigms such as SSVEP and P300, and accurately marking stimulus events to provide a time-locked basis for subsequent signal analysis. Among these, Psychtoolbox and PsychoPy are the two most popular open-source tools currently available, offering precise timing control and flexible stimulus programming interfaces, widely used in academic research [4].

In signal processing and BCI frameworks, MATLAB along with its plugin EEGLAB offers powerful signal processing and graphical analysis capabilities, making it the most classic toolset in the BCI field. In recent years, Python-based open-source ecosystems (such as MNE-Python, Scikit-learn) have gained increasing favor among researchers due to their flexibility and cost-free advantages.

More importantly, the emergence of general-purpose BCI software frameworks has achieved modular integration of data acquisition, processing, and feedback applications. OpenViBE and BCI2000, as two of the most influential open-source platforms, support various acquisition devices and provide graphical workflow design interfaces. This allows researchers to quickly build and test BCI systems without programming from scratch, significantly enhancing development efficiency.

2.3.3. Development trends and challenges

The EEG-BCI hardware and software platform is evolving towards integration, portability, and intelligence. For example, using FPGA and other embedded platforms to generate stimuli and perform real-time decoding can free up computer resources, enhance system portability, and improve real-time performance. However, this platform still faces challenges such as poor stability of dry electrode signals, difficulty in deploying complex algorithms on front-end processors like MCUs, and insufficient cross-platform adaptability of software frameworks. Continuous innovation

in hardware and software platforms is key to the maturation and practical application of BCI technology.

3. EEG signal processing workflow

3.1. Workflow designer program

Two scholars from the New Technologies for Information Society (NTIS) at the University of West Bohemia in the Czech Republic introduced an innovative web-based visual workflow design application called Workflow Designer. This application is specifically designed for constructing, editing, and executing EEG signal processing workflows. In the data processing workflow, offline EEG data is first imported into an internal data structure to enable cross-module data exchange. Then, specific channels (such as the Pz channel) are selected through a channel selection function to reduce data dimensionality. Next, segment extraction is performed to capture stimulus-related time periods, followed by baseline correction. The segments corresponding to target stimuli (such as S2 marker events) are then averaged to enhance event-related potential signals. Finally, the EEGPlot module generates visual charts and outputs the results [5].

3.2. EEG chain new open-source toolkit

Four researchers from Iranian universities have developed EEGChain, an open-source EEGLAB-based toolbox that enables graphical construction and management of batch processing workflows for EEG analysis. It simplifies and standardizes preprocessing through an intuitive GUI, supporting operations such as channel interpolation, filtering, noise and artifact removal, epoching, feature extraction via DWT, and classification with a neural network. The toolbox also offers visualization tools for signal browsing and spectral topography.

Compared to platforms like EEGLAB, FieldTrip, Brainstorm, and MNE, EEGChain emphasizes usability, automation, and reproducibility without coding. It is particularly suited for standardized and repeatable analyses, while alternatives like Workflow Designer cater more to visual prototyping. Future improvements could include integrating more advanced methods such as ICA or microstate analysis, expanding processing blocks, and incorporating external tools like ERPLAB or Python scripts [6].

4. Clinical analysis and disease prediction of EEG signals

Epilepsy is the fourth largest neurological disease globally, affecting about 50 million people. Traditionally, doctors diagnose epilepsy by manually analyzing EEG signals, but this method is time-consuming, prone to errors, and requires significant medical resources. Therefore, the authors propose using deep learning models to automatically identify and classify types of epileptic seizures to improve diagnostic efficiency and accuracy.

An EEG is used to diagnose epilepsy as the test records the electrical activity of the brain. EEG features of patients that present epileptic symptoms differ from those of healthy individuals. EEG activity in epileptic patients is divided into phases: ictal phase, meaning during a seizure; postictal phase, meaning after a seizure; and interictal phase, meaning between seizures [7]. Epileptic seizures can be categorized into various types based on diagnostic findings and their presentation as shown in Figure 4.

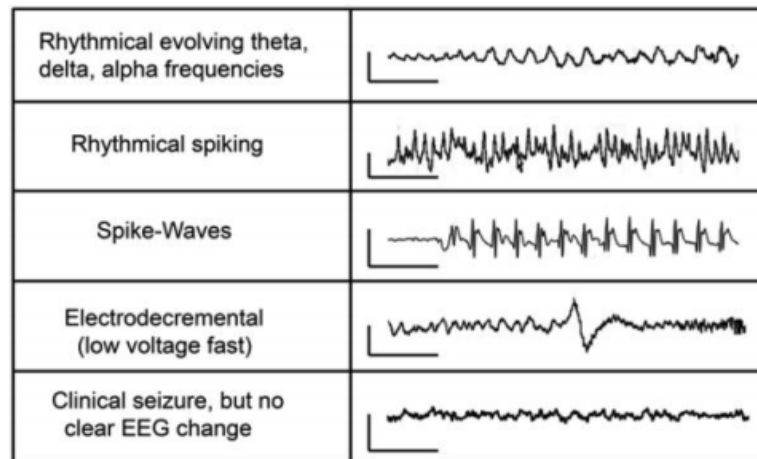


Figure 4. Classification of EEG abnormal patterns related to epilepsy [7]

This study is based on a publicly available epilepsy EEG dataset. It uses CNN and LSTM deep learning models for classifying types of epileptic seizures. The results show that the CNN model has an accuracy rate of 91% (AUC 0.97–1.00), significantly outperforming LSTM (82%), demonstrating the robustness of CNN in processing EEG signals and imbalanced data. To further improve model performance and clinical applicability, data augmentation techniques (such as SMOTE or generative adversarial networks) can be introduced to alleviate issues of small sample size and class imbalance; integrating multimodal clinical features can enhance model generalization ability; and developing lightweight models for deployment on mobile devices or real-time monitoring systems can achieve real-time seizure warning and personalized management, expanding its clinical application scenarios in ICUs or resource-limited areas.

This study validated the feasibility of CNN and LSTM for classifying types of epilepsy on small, imbalanced datasets, with CNN showing particularly outstanding performance and potential for clinical translation. However, it has certain deficiencies in data representation, model robustness, clinical integration, and interpretability. Future research should validate on larger, multicenter datasets and strengthen the integration with clinical practice.

If applied in clinical practice, this study failed to consider actual needs. The model outputs 'seizure type' but does not explain how to integrate it into the clinical decision-making process, nor does it discuss whether the model's output is interpretable (such as visualizing attention maps, feature importance, etc.). Doctors find it difficult to trust 'black box' models. Additionally, there are no comparative experiments with neurologists manually interpreting EEGs, making it impossible to prove whether the model truly excels or aids in manual diagnosis. Therefore, to enter clinical use, the model's interpretability needs to be enhanced by introducing explainability tools like Grad-CAM and SHAP, visualizing the model's focus areas, and designing blind tests to compare the consistency and efficiency of the model's diagnosis with that of doctors [8].

The second approach improves the accuracy and efficiency of detecting epileptic seizures from EEG signals by optimizing feature selection and using artificial neural networks (ANN).

Currently, detection methods based on EEG signals are widely used. However, due to the high dimensionality, nonlinearity, and susceptibility to noise interference of EEG signals, traditional analysis methods have limited effectiveness in processing such complex data. Therefore, this study aims to propose a new method that combines the Artificial Bee Colony Optimization Algorithm (ABC) with ANN. This approach seeks to enhance the accuracy and robustness of epilepsy detection

through intelligent feature selection and efficient classification, providing reliable support for clinical diagnosis.

This study proposes an epilepsy detection method that optimizes feature selection using the ABC and combines it with an ANN. By screening out 97 key features from 178 original features, it achieves a classification accuracy of 90%, significantly reducing data dimensionality and improving computational efficiency. To further enhance model performance and clinical applicability, we propose the following improvement strategies: first, CNN or Transformer deep learning architectures can be used to replace ANN to better capture the spatiotemporal features and long-range dependencies in EEG signals, addressing the lack of research on deep learning models in this task in existing literature; second, dynamic feature updating and online learning mechanisms can be introduced to allow the model to adaptively adjust based on individual patients' EEG characteristics, thus overcoming the limitations of static datasets; finally, the model's interpretability can be enhanced by visualizing the features selected by ABC to intuitively display the key brain regions and feature contributions, thereby increasing clinicians' trust in the model's decisions. These improvements aim to maintain high accuracy while further advancing the development of epilepsy detection systems towards real-time, personalized, and interpretable directions [9]. EEG epilepsy detection process is shown in Figure 5.

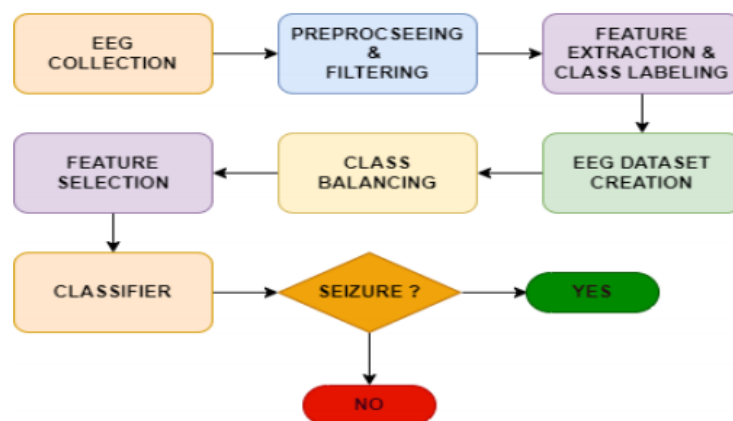


Figure 5. EEG epilepsy detection process [9]

5. Challenges and prospects

5.1. Challenge analysis

Although EEG technology and BCI systems have made significant progress, key challenges remain. EEG signals are susceptible to various types of noise, and while existing filtering methods like ICA are effective, they have high computational complexity, making it difficult to meet real-time requirements. In the future, adaptive filtering combined with Generative Adversarial Networks (GAN) could be explored to dynamically suppress noise. EEG patterns vary significantly among different users, leading to decreased performance of general models. Therefore, we need to develop personalized calibration techniques and transfer learning frameworks to improve model adaptability. Technically, BCI systems require millisecond-level responses, but current deep learning models like CNNs and LSTMs have heavy computational loads. Lightweight models such as EEGNet and edge computing technologies are potential solutions. The processing and decoding of EEG signals aim to serve society, particularly in clinical applications for certain diseases, which are currently the most

needed technologies. However, the high cost and complex operation of current EEG devices limit their application in primary healthcare. Thus, developing low-cost, portable devices and simplifying user interaction processes is necessary. Finally, there are ethical and moral issues. Every technology has two sides; BCI technology involves the collection of neural data, which may lead to privacy leaks and ethical controversies. As we advance, we also need to establish strict data protection regulations and ethical guidelines [10].

5.2. Optimize

Although EEG and BCI technologies show great potential, their further development still faces multiple challenges that require a series of optimizations to enable their integration into real-world clinical applications. EEG signals generally exhibit low quality and poor noise resistance, being susceptible to biological artifacts such as eye movements and electromyographic interference, as well as environmental noise. Traditional methods like Independent Component Analysis (ICA) are computationally complex and often fail to meet real-time processing demands. Future efforts could introduce adaptive filtering combined with Generative Adversarial Networks (GANs) to dynamically learn noise patterns, achieve efficient denoising, improve the signal-to-noise ratio, and reduce computational latency.

Currently, the lack of clinical applicability and model interpretability in EEG-based epilepsy detection and brain-computer interface systems has become a major bottleneck preventing their transition from laboratory research to clinical practice. Most existing deep learning models operate as "black boxes," with opaque decision-making processes. Clinicians require not only predictions but also interpretable reasoning based on physiologically meaningful features—current models often fail to provide explanations consistent with clinical logic. Explainable AI techniques, while advanced in other fields, remain in early stages of application to EEG due to the complexity of spatiotemporal characteristics and the difficulty of aligning results with clinical neurophysiology.

Moreover, single-modality EEG data has inherent limitations in diagnosing complex conditions like epilepsy, which typically requires integrating multimodal information such as MRI/fMRI, patient history, and genetic data. Most current models rely solely on electrophysiological signals and lack effective fusion mechanisms for heterogeneous data. In addition, existing interpretability methods often provide post-hoc explanations rather than incorporating interpretable structures during model design. Future research should focus on developing clinically transparent EEG analysis models, including tailored explainable AI techniques for temporal and cross-channel feature visualization, as well as multimodal data fusion frameworks. These advances will enhance clinicians' trust and facilitate the responsible deployment of AI in epilepsy diagnosis and treatment.

6. Conclusion

EEG signals, as a window into brain activity, have shown great potential in neuroscience, medical diagnosis, and BCI fields. They not only reveal the electrophysiological basis of human thought, emotions, and consciousness but also bring hope for recovery to countless patients in the medical rehabilitation field. Imagine a patient paralyzed from spinal cord injury, who can control a robotic arm to drink water and eat just by using EEG-BCI technology—this scenario, once only found in science fiction, is now gradually becoming a reality in laboratories and clinical settings. EEG technology is redefining the concept of 'disability' and building a technological bridge for patients with motor function disorders to return to society.

This paper improves the noise suppression capability, real-time performance, and individual adaptability of EEG signal processing through a multimodal feature fusion framework, and verifies its effectiveness in epilepsy detection and BCI control experiments. However, EEG technology still faces challenges such as noise interference, individual differences, and real-time requirements. Through interdisciplinary collaboration and technological innovation, EEG and BCI technologies are expected to bring revolutionary breakthroughs in medical rehabilitation and human-computer interaction, ultimately achieving the vision of seamless 'brain-machine' integration.

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