Review

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Integrative neurorehabilitation using brain-computer interface: From motor function to mental health after stroke

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SUMMARY: Stroke remains a leading cause of mortality and long-term disability worldwide, frequently resulting in impairments in motor control, cognition, and emotional regulation. Conventional rehabilitation approaches, while partially effective, often lack individualization and yield suboptimal outcomes. In recent years, brain-computer interface (BCI) technology has emerged as a promising neurorehabilitation tool by decoding neural signals and providing real-time feedback to enhance neuroplasticity. This review systematically explores the use of BCI systems in post-stroke rehabilitation, focusing on three core domains: motor function, cognitive capacity, and emotional regulation. This review outlines the neurophysiological principles underpinning BCI-based motor rehabilitation, including neurofeedback training, Hebbian plasticity, and multimodal feedback strategies. It then examines recent advances in upper limb and gait recovery using BCI integrated with functional electrical stimulation (FES), robotics, and virtual reality (VR). Moreover, it highlights BCI's potential in cognitive and language rehabilitation through EEG-based neurofeedback and the integration of artificial intelligence (AI) and immersive VR environments. In addition, it discusses the role of BCI in monitoring and regulating post-stroke emotional disorders *via* closed-loop systems. While promising, BCI technologies face challenges related to signal accuracy, device portability, and clinical validation. Future research should prioritize multimodal integration, AI-driven personalization, and large-scale randomized trials to establish long-term efficacy. This review underscores BCI's transformative potential in delivering intelligent, personalized, and cross-domain rehabilitation solutions for stroke survivors.

Keywords: neurorehabilitation, neural plasticity, motor dysfunction, cognitive reconstruction, neurofeedback, post-stroke depression

1. Introduction

Stroke is one of the leading causes of mortality and long-term disability worldwide, with its high incidence and associated impairments imposing a substantial burden on individuals, families, and society. According to 2021 statistics, more than 16 million people globally suffer from stroke, and approximately one-third of these patients experience permanent disability (*1*). As a neurovascular emergency, stroke commonly results in motor deficits, cognitive dysfunction, and emotional disturbances. Chronic motor dysfunction, and particularly hemiplegia, affects nearly 30% of stroke survivors, making it one of the most disabling outcomes (*2*). Moreover, post-stroke cognitive impairment (PSCI) is reported in 25% to 80% of patients (*3*), and a study in a Chinese cohort showed that 57.8% of 963 stroke patients exhibited depressive symptoms (*4*). Although conventional rehabilitation approaches, including physical therapy, occupational therapy, and speech therapy, have demonstrated certain benefits, their efficacy is often limited by insufficient individualization, suboptimal therapeutic outcomes, and prolonged recovery periods. Research indicates that approximately 20% to 30% of stroke patients are unsuitable candidates for therapies such as constraint-induced movement therapy (CIMT) and other conventional rehabilitation strategies (*5*).

In recent years, advances in neuroscience and engineering have led to the emergence of brain-computer interface (BCI) technology, which offers novel therapeutic avenues for stroke rehabilitation. BCIs decode neural signals and either translate them into commands for external devices or use them directly

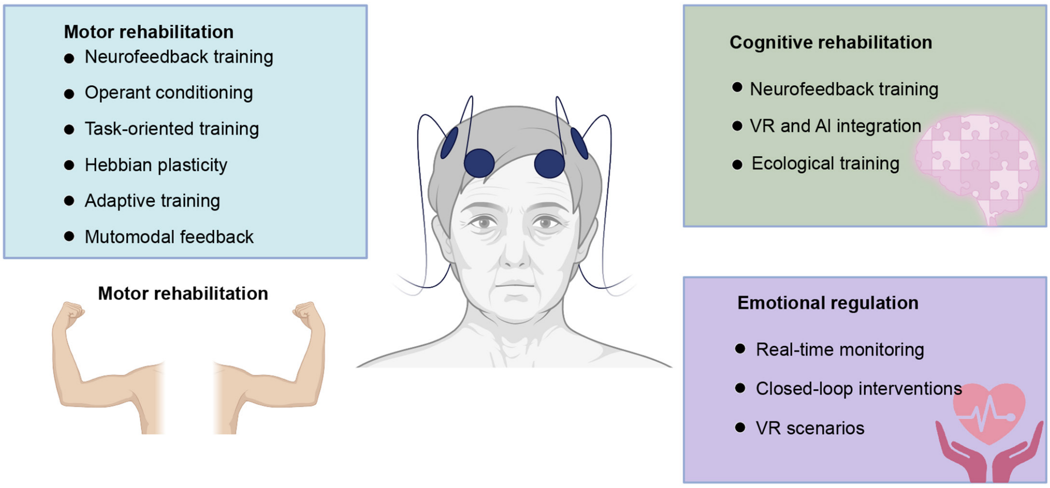

Figure 1. Mechanisms of brain-computer interface applications across motor, cognitive, and emotional domains in stroke rehabilitation.

for neurofeedback, thereby enhancing neuroplasticity and functional recovery (*6*). BCI applications have displayed considerable potential in motor recovery, cognitive training, and emotional regulation. The rehabilitation needs of stroke patients are complex and multidimensional, encompassing motor function restoration, cognitive reorganization, and emotional stabilization (*7*). These domains are highly interrelated. For instance, cognitive impairments may reduce the motivation for motor training, while emotional disturbances can exacerbate functional limitations. Consequently, the development of interdisciplinary and personalized rehabilitation strategies based on BCI technology has become a critical focus of contemporary research.

This review investigates the role of BCI in stroke rehabilitation by examining its applications across motor, cognitive, and emotional domains (Figure 1). Specifically, it explores BCI-driven motor rehabilitation mechanisms and techniques, assesses cognitive and emotional training potentials, and discusses the integration of artificial intelligence (AI) and virtual reality (VR) into BCI-based interventions. Finally, it outlines the technical and clinical challenges that remain and proposes future research directions aimed at advancing this promising field.

2. BCI-based motor function rehabilitation

2.1. Principles of BCI rehabilitation for motor dysfunction

Motor dysfunction is one of the most common and debilitating sequelae of stroke, severely compromising patients independence in daily living. BCI-based rehabilitation systems offer innovative and effective approaches to restoring motor function by enhancing neural plasticity through real-time brain signal interaction.

2.1.1. Neurofeedback training

Neurofeedback training is a foundational mechanism in BCI-based motor rehabilitation, allowing patients to self-regulate brain activity by observing real-time neural signals (*8*). By visualizing the activation of motor-related cortical regions on a screen, patients can reinforce motor-related brain activity through motor imagery (*9*). This technique enhances motor intention and promotes functional reorganization of cortical networks (*10*). Repeated neurofeedback sessions have been shown to reactivate impaired motor areas, leading to measurable improvements in motor performance (*11*).

2.1.2. Operant conditioning

Operant conditioning utilizes a reward-based mechanism to reinforce desired neural patterns (*12*). In the BCI context, when patients successfully generate motor intention, such as imagining raising of the arm, the system delivers visual, tactile, or electrical feedback as reinforcement (*13*). This positive feedback not only boosts patient confidence but also reinforces motor circuit reorganization through reinforcement learning principles (*14*).

2.1.3. Repetitive participation and task-oriented training

The principle of "use it or lose it" underscores the necessity of repeated motor activity to enhance neural circuits. BCI systems enable patients to repeatedly engage in task-oriented training, such as controlling a virtual arm to perform grasping tasks using brain signals (*15*). Such task-oriented practice facilitates the remodeling of key motor pathways, including the corticospinal tract and corpus callosum, ultimately improving motor coordination and accuracy (*16*).

2.1.4. Hebbian plasticity

Hebbian plasticity, commonly summarized as "neurons that fire together, wire together," is another core concept in BCI motor rehabilitation (*17*). Stroke survivors often experience a disconnect between motor intention and actual movement, resulting in diminished sensory feedback to the motor cortex (*18*). BCI systems restore this feedback loop *via* robotic or tactile stimulation, re-establishing the association between intention and feedback, thereby promoting cortical disinhibition and functional recovery (*17,19*).

2.1.5. Personalized and adaptive training

Due to individual differences in stroke lesion location and severity, rehabilitation protocols must be highly individualized. Modern BCI platforms employ machine learning algorithms to dynamically adjust training difficulty and feedback modalities. Patients with more severe impairments may receive simplified tasks with intensive feedback, whereas those with better residual function can be challenged with more complex tasks to further enhance recovery potential.

2.1.6. Multimodal feedback integration

Conventional BCI systems often rely solely on visual feedback. However, integrating multimodal stimuli, including tactile, auditory, and VR-based feedback, has been shown to significantly enhance therapeutic outcomes (*20,21*). VR technologies, in particular, offer immersive environments that increase training engagement and perceived agency (*22*). This multisensory feedback fosters deeper neural engagement and promotes more effective reorganization of motor networks.

2.2. Advances in BCI-based motor rehabilitation

Stroke-related motor dysfunction significantly limits activities of daily living and social participation. Upper limb impairments are particularly prevalent, affecting approximately 80% of survivors (*23*). Recent innovations in BCI motor rehabilitation have incorporated neurofeedback, functional electrical stimulation (FES), robotic systems, and VR, expanding therapeutic possibilities.

2.2.1. BCI in upper limb rehabilitation: Clinical applications

Initial BCI research primarily focused on recovery of upper limb function, exploring how decoding brain activity could restore voluntary motor control. Buch *et al*. were among the pioneers utilizing magnetoencephalography (MEG) to assess sensorimotor rhythm (SMR) training in chronic stroke patients, who displayed increased motor cortex activation following BCI training (*24*). Later, Ang *et al*. integrated electroencephalography (EEG)-based BCI with the MIT-Manus robotic system, and they reported a 4.9-point average improvement in Fugl-Meyer Assessment (FMA) scores after 12 sessions (*25*). However, a meta-analysis revealed that training of a shorter duration (< 12 hours) was associated with greater functional gains, suggesting an optimal training window (*26*).

2.2.2. Motor recovery with FES

FES complements BCI-based rehabilitation by executing movements corresponding to decoded motor intentions. Chung *et al*. found that BCI-triggered FES improved postural stability and gait coordination in chronic hemiplegic patients, as evinced by improved timed up and go (TUG) test scores (*27*). FES also enhances Hebbian plasticity *via* closed-loop feedback, facilitating cortical reorganization (*28*). A randomized controlled trial (RCT) by Jiang *et al*. further confirmed that BCI-FES training significantly improved hand grip strength and enhanced alpha wave activity in the motor cortex, indicating that this combined approach facilitates motor network reorganization (*29*).

2.2.3. Integration of robotic assistance and VR

Robotic devices are increasingly being integrated into BCI systems to provide precise mechanical support and stimulate neuroplasticity (*30*). Ramos-Murguialday *et al*. developed a BCI-controlled robotic arm, resulting in notable improvements in hand strength and movement precision (*31*). Functional magnetic resonance imaging (fMRI) results confirmed increased activation in motor-related brain areas post-training (*32*). VR-enhanced BCI systems further improve user engagement and realism. For instance, Pichiorri *et al*. combined VR with motor imagery (MI) tasks, which improved both MI success rates and motor function (*33*). Immersive VR enhances the realism of imagined movements, thereby optimizing training outcomes (*22*).

2.2.4. Gait rehabilitation and locomotion training

Gait impairment is a common post-stroke functional deficit, characterized by reduced step length, decreased gait speed, and poor balance control, severely affecting independent ambulation (*34*). BCI-based gait rehabilitation has emerged as a key research focus. Tang *et al*. explored a BCI gait rehabilitation system combining MI with visual feedback. After six weeks of training, significant improvements were observed in TUG test performance and gait stability and were correlated with increased corticospinal activity in the contralateral primary motor cortex (M1) (*34,35*). Kim *et al*. further developed a BCI-integrated exoskeleton-based lower limb training platform, allowing patients to control the exoskeleton for gait training, which led to significant improvements in gait accuracy and stability (*36*).

2.2.5. Multimodal integration and personalized rehabilitation approaches

Recent developments emphasize multimodal integration and personalized training protocols. Dual-modality BCI systems combining EEG and functional near-infrared spectroscopy (fNIRS) significantly improve the accuracy of motor intention decoding. For example, Kwak *et al*. proposed an fNIRS-guided attention network (FGANet) system that improved MI task accuracy by 4.0% and mental arithmetic performance by 2.7% compared to conventional models (*37*). Moreover, adaptive BCI systems utilizing AI can tailor task difficulty and feedback in real time. Zhang *et al*. found that such systems improved training efficiency and patient outcomes (*38*), highlighting the advantages of individualized rehabilitation.

2.2.6. Clinical validation and long-term outcomes

Despite promising results in laboratory settings, clinical evidence remains limited. A meta-analysis by Cervera *et al*. found that BCI interventions produced a standardized mean difference (SMD) of 0.79 in FMA for upper extremity (FMA-UE) scores, a result comparable to conventional therapies such as mirror therapy and CIMT (*39*). However, small sample sizes and a lack of long-term follow-up limit generalizability. To address this gap, Wang *et al*. conducted a multicenter RCT involving 296 stroke patients, comparing a BCI rehabilitation group with a conventional rehabilitation group (*40*). After one month, the BCI group showed significantly greater improvements in FMA-UE scores (13.17 *vs*. 9.83; between-group difference: 3.35; 95% CI: 1.05–5.65; P = 0.0045).

3. BCI-based cognitive and language rehabilitation

3.1. Mechanisms and applications in cognitive rehabilitation

Cognitive rehabilitation is a vital aspect of post-stroke recovery, and yet conventional methods often lack precision and have limited efficacy. In contrast, BCI technology offers the significant potential to enhance cognitive function in stroke patients, particularly through neurofeedback-based cognitive assessment and memory training (*41*). Studies suggest that BCI systems utilizing theta and alpha waves — key neural oscillations tied to memory encoding — can precisely control the timing of item presentation in memory tasks, leading to substantial improvements in memory performance (*42,43*).

3.1.1. Neural features of PSCI and EEG-based targeting

PSCI typically affects domains such as attention, memory, executive function, and language processing (*44*). These deficits typically arise from disrupted neural networks or functional impairments caused by brain damage. For example, dysfunction in the frontal and parietal lobes often leads to attention deficits and executive dysfunction, while hippocampal atrophy is strongly associated with memory decline.

BCI systems offer dynamic assessment of these impairments by decoding EEG patterns and other neural markers. Research has shown that variations in beta/theta power correlate with attentional control, while alpha wave activity is linked to memory performance *(45,46*). By modulating these EEG patterns, BCI systems can target specific cognitive impairments, offering tailored therapeutic interventions that enhance recovery.

3.1.2. Neurofeedback and modulation strategies

Neurofeedback training serves as a cornerstone of BCI-based cognitive rehabilitation, providing real-time feedback that allows patients to consciously regulate abnormal neural activity. Evidence suggests that this approach can improve attention and memory function in stroke populations (*47*). For example, neurofeedback interventions have resulted in measurable improvements in both short-term and long-term verbal memory in patients and healthy controls (*48*). A case study by Mroczkowska *et al*. demonstrated that adjusting the beta/theta ratio in the C3 cortical region significantly enhanced attentional control and information processing efficiency (*43*). Moreover, neurofeedback strategies targeting specific cognitive domains have yielded promising results. In one study, patients trained to increase beta power in the prefrontal cortex *via* neurofeedback showed significant improvements in executive function task performance (*49*). These findings highlight the promise of BCI-based neurofeedback in restoring cognitive function.

3.1.3. Role of VR and AI in adaptive cognitive training

The incorporation of VR into BCI-based cognitive rehabilitation enables the creation of immersive environments for ecologically valid cognitive training. By simulating real-world scenarios such as virtual shopping, navigation, and social interactions, VR enables patients to engage in practical cognitive exercises (*50*). A recent study found that a BCI-VR system significantly improved multitasking abilities and spatial memory (*51*). Pichiorri *et al*. further developed VR-based cognitive tasks within a BCI system, leading to enhanced attention control and working memory performance in stroke patients (*33*).

In addition, integrating AI into BCI systems allows for dynamic adjustments to training protocols based on real-time patient feedback. Machine learning algorithms can detect cognitive fatigue or plateau states by analyzing EEG patterns and dynamically modulate training intensity, thereby maximizing training efficiency (*52*). Despite these promising results, large-scale clinical trials need to be conducted to validate these technologies and expand their clinical applications.

3.2. Exploration of BCI-based language rehabilitation

Language impairment, a frequent and complex consequence of stroke, affects approximately 30% of patients during the acute phase, with many experiencing persistent deficits in comprehension or expression during long-term recovery (*53-55*). While conventional approaches such as speech-language therapy (SLT) and computer-assisted language training (CALT) offer some benefits, their effectiveness is often limited by low patient adherence, insufficient personalization, and marginal improvements (*56*). BCI technology offers a novel, targeted approach to address these challenges.

3.2.1. Characteristics of aphasia and BCIs applicability

Aphasia, a multifaceted neurological language disorder, impairs both expressive abilities (*e.g.*, word retrieval and articulation) and comprehension (*e.g.*, semantics and syntax). Its manifestations vary depending on the location of brain damage, with lesions in Brocas area typically linked to expressive aphasia and damage to Wernickes area associated with comprehension difficulties (*57*).

BCI technology enhances rehabilitation by capturing and decoding neural signals related to language processing, providing real-time feedback to strengthen neural activity and connectivity. Both EEG and fNIRS have proven effective in detecting changes in neural activity within Brocas and Wernickes areas, providing a basis for designing individualized neurofeedback interventions (*58*).

3.2.2. Neurofeedback-based language rehabilitation

Neurofeedback training is a pivotal technique in BCI-based language rehabilitation, enabling patients to monitor and regulate brain activity associated with language processing. For example, Mroczkowska *et al.* showed that modulating beta wave activity at the C3 electrode site significantly improved word selection and generation in patients with expressive aphasia (*43*). Moreover, neurofeedback targeting relative alpha wave power in the occipital lobe yielded moderate improvements in naming, image and color recognition, sentence completion, and language fluency (*59*). In a 10-session intervention, training to enhance the beta/theta ratio at the C3 EEG electrode site significantly improved speech fluency, word retrieval speed and accuracy, and comprehension of complex syntactic structures (*43*). However, the generalizability of these findings remains limited by small sample sizes and lack of a long-term follow-up.

4. BCI-based emotional regulation and mental health interventions

4.1. Impact of post-stroke emotional disorders

Emotional disturbances such as post-stroke depression (PSD) and anxiety significantly affect rehabilitation outcomes by reducing motivation, adherence, and overall quality of life. Studies estimate that 25% to 50% of patients experience depression during the acute phase, with approximately 30% continuing to suffer in the chronic phase (*60,61*). Depression often manifests as negative thought patterns, diminished motivation, and social withdrawal, all of which indirectly impede the progress of rehabilitation.

Similarly, post-stroke anxiety (PSA) affects 18% to 34% of survivors within the first year, with rates remaining stable up to five years post-stroke (*62-66*). Patients with PSA frequently exhibit excessive worry about their prognosis, including fears of recurrence, returning to work, falling, or losing independence. This anxiety can exacerbate depression and cognitive impairment, further worsening outcomes (*63*).

4.2. Real-time emotional monitoring and closed-loop regulation techniques

BCI technology enables real-time monitoring of emotional states by decoding key brain activity features. EEG signals, and particularly alpha and beta waves, are widely studied in emotional regulation. Low alpha-wave activity is typically linked to anxiety and tension, while high alpha-wave activity indicates relaxation and stability. Increased frontal midline theta power, conversely, correlates with positive emotions (*67*).

To improve emotion detection accuracy, recent BCI models have integrated multimodal signals such as EEG, heart rate variability (HRV), and electrodermal activity (EDA). Reduced HRV is often indicative of psychological distress, while heightened EDA is associated with anxiety (*68*). This integrative approach provides a more comprehensive assessment of emotional dynamics. In addition to monitoring, BCI systems with affective closed-loop interactions show promise in emotional regulation. For example, participants have successfully modulated musical feedback by recalling emotionally salient memories, illustrating the potential of BCI-assisted emotional self-regulation (*69*). Closed-loop systems can also detect negative emotions and trigger real-time interventions — such as mood-regulating music, VR-based meditation environments, or neurofeedback training — to adjust EEG activity and restore emotional balance (*70*). Recent advances in AI and machine learning have significantly enhanced

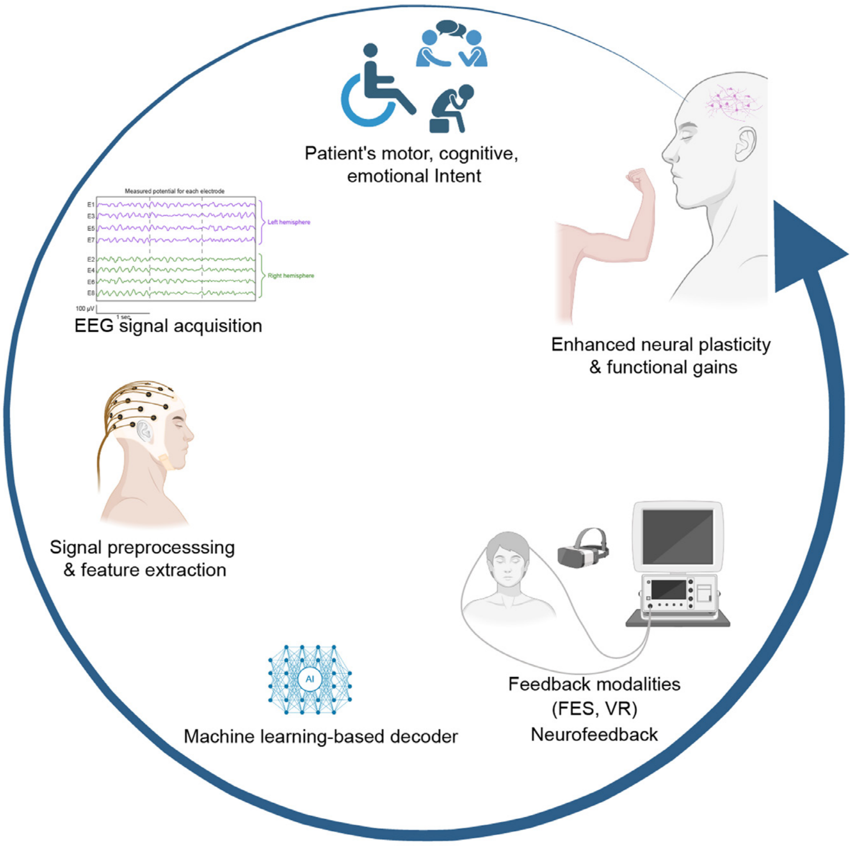

Figure 2. A conceptual framework of brain-computer interface-driven neurorehabilitation in stroke.

the accuracy and efficiency of real-time EEG-based emotion recognition within BCI systems. Self-supervised learning models, which reduce the need for large labeled datasets, have shown promise in decoding affective states by learning internal signal representations through signal transformation tasks prior to fine-tuning for emotion classification (*71*). Similarly, deep 3D convolutional neural networks with multiscale kernels have demonstrated a high level of accuracy — up to 95.67% on the DEAP dataset — by capturing complex spatiotemporal EEG patterns (*72*). Transformer-based architectures, known for their sequence modeling capabilities, have also emerged as powerful tools for EEG-based decoding of emotion, enabling more scalable and generalizable models for real-time applications (*73*).

One proof-of-concept study integrated real-time fMRI-based neurofeedback (rtfMRI-NFB) with both musical stimuli and immersive virtual environments, demonstrating the feasibility of such multimodal closed-loop systems. This interface employed both localized (region of interest, or ROI) and distributed (support vector machine, or SVM) neural activity analyses, enabling more precise detection and modulation of emotion-related brain states (*70*). The combination of BCI and VR technology offers particular advantages in managing emotional dysregulation. Through BCI-mediated neurocognitive training, both the patient and the system help to modify neuronal activity, which can lead to significant reductions in anxiety-related symptoms (*74*). In one study, a VR scenario displaying calming landscapes (*e.g.*, forests or oceans) was activated when anxiety was detected, significantly reducing anxiety scores and enhancing well-being (*75*). Similarly, SMR-BCI systems, which decode motor-related alpha and beta waves to control external devices like robots or exoskeletons, suggest broader applications in emotional rehabilitation (*76*). These findings highlight BCIs potential to deliver integrated, interactive, and patient-centered mental health interventions post-stroke.

5. Discussion

In recent years, BCI technology has made remarkable progress in enhancing motor, cognitive, and emotional recovery following stroke. As an interdisciplinary tool integrating neuroscience, engineering, and AI, BCI has shown significant potential to reshape conventional neurorehabilitation paradigms (as illustrated in Figure 2). By enabling real-time decoding of neural activity and providing personalized feedback, BCI-based interventions offer novel and precise rehabilitation strategies across multiple functional domains. Despite these promising developments, several technical and clinical challenges must be addressed to fully realize the clinical potential of BCI systems. One of the primary limitations is the accuracy and stability of signal decoding. EEG-based motor intention signals are highly susceptible to noise and artifacts, which can compromise decoding reliability and reduce system responsiveness. Future research should prioritize the integration of multimodal data sources, such as EEG combined with fNIRS or fMRI, to enhance signal fidelity and improve the precision of motor intention and emotional state recognition.

Another critical area where advances are needed is the personalization of rehabilitation protocols. Current BCI interventions often employ static, one-size-fits-all task models, which limit adaptability to individual patient profiles. The integration of AI and machine learning can address this issue by enabling real-time adaptation of training difficulty, feedback type, and task complexity based on patient performance and cognitive-emotional states. This approach can significantly improve training efficiency and patient engagement. In addition, the clinical translation of BCI systems remains hindered by practical limitations. Most current systems are confined to research or laboratory settings due to their complexity, bulkiness, and cost. To increase accessibility and facilitate home-based, long-term rehabilitation, wireless, lightweight, and cost-effective BCI devices need to be developed. Advances in wearable sensor technology and mobile computing may facilitate the design of portable, user-friendly BCI platforms suitable for continuous at-home use.

A major gap in the field is the lack of large-scale, multicenter RCTs to establish the long-term efficacy and safety of BCI interventions. Existing studies are often limited by small sample sizes, heterogeneous methodologies, and follow-up of an insufficient duration. Future research should focus on conducting well-designed clinical trials to evaluate both short- and long-term outcomes across diverse patient populations. Additionally, the development of standardized clinical guidelines and training protocols will be essential to the widespread adoption of BCI technology in routine rehabilitation practice.

6. Conclusion

In summary, BCI technology represents a transformative innovation in stroke rehabilitation, offering integrated and adaptive solutions for motor function recovery, cognitive enhancement, and emotional regulation. BCI technology currently has limitations, but ongoing advances in neuroscience, AI, VR, and wearable systems should help to further refine BCI platforms. In the future, BCI is poised to become a cornerstone of personalized, intelligent neurorehabilitation, providing stroke survivors with more effective, accessible, and holistic recovery pathways.

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