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Review article

BRAIN-COMPUTER INTERFACES IN NEUROREHABILITATION FOR CENTRAL NERVOUS SYSTEM DISEASES: APPLICATIONS IN STROKE, MULTIPLE SCLEROSIS AND PARKINSON'S DISEASE

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Abstract: Brain-computer interfaces (BCIs) represent an innovative approach to neurorehabilitation for neurological conditions, particularly stroke, multiple sclerosis, and Parkinson's disease. This paper provides a comprehensive analysis of current BCI applications, technological developments, and clinical outcomes in these conditions. Recent advances in electroencephalography-based BCIs have demonstrated promising results, with classification accuracies exceeding 90% in stroke rehabilitation and comparable performance in multiple sclerosis and Parkinson's disease. Meta-analyses of stroke rehabilitation trials (n=235) indicate significant motor function improvements, with standardized mean differences of 0.79 in upper limb assessment scores compared to conventional therapy. Disease-specific challenges necessitate tailored approaches, while hybrid systems combining multiple signal types and integration with virtual reality or robotic assistance enhance therapeutic potential. The development of portable, home-based systems offers increased therapy intensity but raises concerns about remote monitoring and safety protocols. This review synthesizes current evidence supporting BCI applications in neurorehabilitation and highlights critical areas for future research, including cognitive rehabilitation optimization and the standardization of outcome measures for cross-condition comparison.

Keywords: brain-computer interface, neurorehabilitation, stroke, multiple sclerosis, Parkinson's disease, motor imagery, neuroplasticity.

INTRODUCTION

Diseases of the central nervous system, such as stroke, multiple sclerosis (MS), and Parkinson's disease (PD), represent significant global health challenges, with diverse pathologies affecting neural structure and function. Stroke remains one of the leading causes of adult disability, affecting approximately 16.3 million people worldwide annually, as estimated by the WHO. Half of all stroke survivors experience lasting disabilities that impact motor and cognitive functions (1). The challenges of stroke-related neuroplasticity necessitate effective rehabilitation methods that target damaged neural pathways to restore motor function and improve quality of life.

Multiple sclerosis, affecting roughly 1.8 million people globally (WHO), causes neurodegeneration and demyelination, disrupting motor and sensory processing and leading to physical and cognitive impairments (2). Current MS therapies often prove insufficient in addressing progressive motor decline and cognitive dysfunction (3). Parkinson's disease affects approximately 1% of individuals over 60, causing motor deficits due to the degeneration of dopamine-producing neurons, which results in tremors, rigidity, and bradykinesia (4). Traditional rehabilitation methods show limitations in providing targeted neurostimulation for PD's progressive symptoms (5).

These conditions present substantial challenges in neurorehabilitation, as existing approaches often fail to achieve long-term recovery due to the brain's limited capacity for self-repair. While conventional rehabilitation remains a cornerstone of treatment for these neurological disorders, its limitations in addressing disease progression highlight the need for complementary therapeutic approaches to enhance rehabilitation outcomes.

Brain-computer interfaces (BCIs) establish direct communication channels between the brain and external devices, enabling control of assistive technologies and therapeutic systems through neural signal interpretation. These systems fall into two main categories:

invasive and non-invasive interfaces. Electroencephalography (EEG) is a widely used non-invasive BCI method, valued for its cost-effectiveness, safety, and practical implementation (6). Motor imagery (MI)-based BCIs show promise in motor function restoration by leveraging the brain's ability to activate motor regions during imagined movement. These systems detect and translate neural activity into physical or virtual actions (7). EEG-based BCIs effectively capture motor-related signals, particularly sensorimotor rhythms associated with imagined movement, thereby engaging neuroplastic mechanisms that promote motor recovery (8, 9).

BCIs offer significant value in neurorehabilitation by harnessing neuroplasticity—the brain's ability to reorganize and strengthen neural connections through activity (10). In stroke rehabilitation, BCIs facilitate repetitive, targeted activation of specific neural pathways, reinforcing motor intention through movement simulation tasks. This process, combined with BCI feedback via visual or robotic-assisted systems, supports neural circuit reorganization and functional recovery (11, 12).

This paper examines recent developments in BCI-based neurorehabilitation for stroke, MS, and PD, analyzing clinical applications and emerging research directions. The analysis covers EEG-based BCI applications in motor, cognitive, and speech rehabilitation, including MI-based BCIs for upper limb motor recovery and EEG-based network analysis in chronic stroke patients. Additionally, it explores BCI integration with virtual reality (VR) and robotics—technologies that enhance user engagement and promote neuroplasticity through interactive therapeutic environments (13). Given the experimental nature of BCI-based treatments, this review also addresses technical challenges related to neurological signal accuracy and user-specific calibration, as well as ethical considerations in clinical rehabilitation (14, 15).

By evaluating current BCI methodologies, this paper provides a comprehensive analysis of optimal BCI integration in neurorehabilitation, offering insights for researchers and clinicians advancing this field.

BRAIN-COMPUTER INTERFACE TECHNOLOGY IN NEUROREHABILITATION

Brain-computer interfaces (BCIs) have emerged as innovative tools in neurorehabilitation by establishing direct communication pathways between the brain and external devices. These systems have shown significant development in recent years, offering various approaches to facilitate motor recovery and neural plasticity in patients with neurological conditions. A bibliometric analysis by Angulo Medina et al. (15) revealed a substantial increase in BCI research focused on rehabilitation applications, particularly in motor recovery and cognitive rehabilitation. The integration of advanced signal processing techniques and artificial intelligence has expanded these systems' capabilities, enabling more precise and adaptive rehabilitation protocols (16). Understanding the different types of BCIs, their underlying signal acquisition methods, and the current technical challenges is essential for advancing their clinical implementation.

Types of BCIs Used in Rehabilitation

Motor Imagery (MI)

Motor imagery-based BCIs demonstrate value in neurorehabilitation, especially for stroke recovery. Research has identified distinct patterns of neural activation during MI tasks in stroke patients, showing increased activity in the contralateral motor area, while healthy controls exhibit higher activity in the ipsilateral motor area (8). MI-BCIs show notable effectiveness in the beta band, where stroke patients demonstrate significantly higher clustering coefficients during MI tasks compared to active and passive movements. Studies reveal that node strength in the gamma band during MI paradigms shows marked improvement over both active and passive paradigms, suggesting enhanced neural engagement during imagery-based tasks (8). Miladinović et al. (17) conducted a systematic study of temporal parameters in MI-BCI systems, determining that time windows of 1-2 seconds provide an optimal balance between classification accuracy and system responsiveness. Their research compared multiple classification approaches, with linear discriminant analysis showing superior performance for MI task classification.

Passive BCIs

Passive BCIs monitor brain states without requiring active user commands, offering an alternative approach to rehabilitation. Simon et al. (14) emphasize these systems' particular value for patients with severe motor impairments who may find active BCI control challenging. Recent developments have integrated passive BCIs with virtual reality and robotic systems to create more engaging rehabilitation environments (13) for patients with limited abilities, including those with complete paralysis.

Closed-loop BCIs

Closed-loop BCI systems provide continuous adaptation based on patient performance and physiological feedback. Saga et al. (18) developed an approach combining EEG and EMG in a closed-loop system, demonstrating feasibility for continuous motion control. Zhan et al. (9) provided evidence that BCI-FES (functional electrical stimulation) systems can improve motor function in chronic stroke patients, showing significant improvements in Fugl-Meyer assessment scores compared to FES-only controls.

Signal Acquisition and Processing Techniques

EEG remains the primary signal acquisition method in rehabilitation BCIs due to its practical advantages in clinical settings. A comprehensive bibliometric analysis by Tsiamalou et al. (6) identified EEG as the most significant input method for BCIs, citing its non-invasive nature, accessibility, and cost-effectiveness. Recent advances in signal processing have focused on improving classification accuracy through various methods. Guerrero-Mendez et al. (19) investigated the effects of temporal and frequency segmentation combined with common spatial pattern methods for movement identification, demonstrating the importance of dynamic temporal segmentation strategies. Additionally, Rosanne et al. (20) introduced novel features based on EEG amplitude modulation dynamics, showing significant improvements in classifier performance when combined with conventional power spectral features.

Challenges and Limitations

Signal Noise and Classification Accuracy

BCI systems continue to face significant technological challenges despite recent advances. Simon et al. (14) identified several critical barriers to widespread BCI adoption, including signal quality variability and maintaining consistent classification accuracy across sessions. Miladinović et al. (17) specifically addressed these issues in their work on optimizing real-time MI-BCI performance, highlighting the balance between classification accuracy and system responsiveness.

User Adoption

Gunduz et al (21) reviewed challenges in novel stroke neurorehabilitation approaches, emphasizing the heterogeneity of patient populations and the need for standardized methodologies. Their work highlights the importance of biomarker-driven individualized approaches and large-scale clinical trials with well-targeted patient populations.

Ethical and Practical Barriers

A recent bibliometric analysis by Angulo Medina et al. (15) identified system inefficiencies and accessibility issues as key challenges. The authors emphasize the need for expanding global participation in BCI research and development, particularly in underrepresented regions, while addressing ethical considerations, including data privacy and equitable access to BCI technologies. The scientific community continues to evaluate the long-term efficacy of BCIs and their impact on rehabilitation alongside existing treatment options (15, 22).

BRAIN-COMPUTER INTERFACE APPLICATIONS IN STROKE REHABILITATION

Motor Rehabilitation

Mechanisms of BCI in Post-Stroke Recovery

BCIs have demonstrated significant potential as therapeutic interventions for post-stroke motor recovery. These systems facilitate neuroplasticity through direct neural feedback loops, enabling patients to engage in rehabilitation exercises even without voluntary movement capacity (14). The therapeutic mechanism relies on coupling intended motor actions with sensory feedback, reinforcing neural pathways involved in motor control. Recent neurophysiological studies have revealed underlying mechanisms of BCI-mediated recovery. Su et al. (8) documented significant alterations in brain network connectivity during BCI interventions, particularly in the beta frequency band. Their findings showed enhanced clustering coefficients during motor imagery tasks compared to active and passive movements, suggesting distinct patterns of functional reorganization. These studies observed increased activity in contralesional motor areas, indicating potential compensatory mechanisms in the recovery process.

Clinical Applications and Intervention Protocols

Several therapeutic protocols have been developed for BCI-mediated stroke rehabilitation. MI-BCIs have shown promise in clinical settings. In a significant clinical study, Irimia et al. (12) evaluated MI-BCI control in stroke patients using the recoveri X system. Their research demonstrated high classification accuracies (mean 87.4%) across patient sessions, with peak accuracies exceeding 96%. Notably, stroke patients achieved higher control accuracies than previously reported in healthy subjects, potentially due to increased therapeutic motivation. Their intervention protocol combined motor imagery with simultaneous functional electrical stimulation (FES) and visual feedback through simulated environments, creating a comprehensive sensorimotor feedback loop. Building on these findings, Kaviri and Vinjamuri (16) implemented advanced source localization techniques with a neural network architecture, achieving 91.03% classification accuracy with dipole fitting. Their methodology demonstrated superior performance compared to conventional approaches in differentiating motor imagery patterns. The integration of multiple physiological signals has enhanced therapeutic applications. Saga et al. (18) developed a hybrid system combining EEG and EMG, enabling continuous motion detection and feedback, facilitating more natural movement patterns during rehabilitation sessions.

Clinical Outcomes and Therapeutic Efficacy

Meta-analytic evidence supports the clinical efficacy of BCI interventions in post-stroke motor recovery. A systematic review of nine randomized controlled trials (n = 235) by Cervera et al. (10) demonstrated a standardized mean difference of 0.79 in upper limb Fugl-Meyer Assessment scores compared to control interventions, suggesting clinically meaningful improvements in motor function following BCI therapy. Further evidence comes from comparative effectiveness research. Ang et al. (11) showed that BCI-triggered robotic feedback achieved comparable motor gains to intensive robotic therapy while requiring significantly fewer movement repetitions (136 versus 1,040 repetitions per session), suggesting enhanced therapeutic efficiency through more precise timing of sensorimotor feedback.

Cognitive and Speech Rehabilitation

Cognitive Recovery Outcomes

BCI interventions have shown efficacy in addressing post-stroke cognitive deficits. Controlled trials of EEG-based neurofeedback training have demonstrated specific improvements in working memory and short-term memory function (23). These cognitive improvements appear to be protocol-specific, with effectiveness noted in interventions targeting upper alpha frequency modulation.

Speech and Language Recovery

Recent technological advances have expanded BCI applications to speech rehabilitation. Systematic investigation of BCI-based communication systems has demonstrated feasibility for patients with severe post-stroke speech impairments (24). These systems utilize neural signal processing to decode speech intentions, providing alternative communication pathways for severely affected patients.

Recent Clinical Advances and Future Directions

Protocol optimization continues to advance therapeutic applications. Miladinović et al. (17) identified optimal temporal parameters for real-time MI-BCI implementation, determining that 1-2 second processing windows maximize both classification accuracy and therapeutic responsiveness. BCI intervention accessibility has improved through technological developments. Craik et al. (25) validated a low-cost, mobile EEG-based system achieving clinical-grade signal quality (SNR = 121 dB, CMRR = 110 dB) while maintaining closed-loop functionality. These developments suggest potential for expanded therapeutic applications in outpatient and home-based settings. Despite these advances, significant challenges remain in protocol standardization and clinical implementation (14). Future research directions include the development of adaptive therapeutic protocols and integration of artificial intelligence for enhanced signal processing. Additionally, large-scale clinical trials are needed to establish optimal treatment parameters and identify patient populations most likely to benefit from BCI interventions.

BRAIN-COMPUTER INTERFACE APPLICATIONS IN MULTIPLE SCLEROSIS REHABILITATION

Motor Rehabilitation

BCIs for Motor Impairment in MS

Multiple sclerosis (MS) presents unique rehabilitation challenges due to its progressive nature and variable symptom presentation. Brain-computer interface technology has emerged as a promising intervention for addressing motor impairments in MS patients. Carrere et al. (26) investigated BCI combined with functional electrical stimulation (FES) for gait rehabilitation in MS patients, demonstrating statistically significant post-treatment improvements in gait speed and walking ability. Their findings showed earlier event-related desynchronization onset latency after treatment, suggesting changes in functional brain connections involved in sensorimotor rhythm modulation. Recent feasibility studies have shown promising results for BCI application in MS patients. Russo et al. (27) demonstrated that neural sources generating motor imagery originated from similar motor areas in MS patients compared to neurotypical participants, though with notable differences in alpha power during imagery tasks, indicating preserved motor imagery circuits for BCI control despite disease progression.

Neuroplasticity and MS

Evidence suggests specific neuroplastic mechanisms influenced by BCI interventions in MS patients. Pinter et al. (28) examined the effects of EEG-based neurofeedback training through fMRI studies in MS patients. Their research revealed increased fractional anisotropy and functional connectivity within the salience and sensorimotor networks following successful BCI training. These structural and functional changes correlated with cognitive improvements, suggesting beneficial neuroplastic adaptations from BCI interventions.

Cognitive Rehabilitation

Memory and Executive Function Training

Cognitive impairment affects a significant proportion of MS patients, particularly impacting attention, processing speed, and executive function. Kober et al. (23) demonstrated significant improvements in long-term memory and executive functions through EEG-based neurofeedback training in MS patients. These improvements occurred specifically in patients who successfully learned to self-regulate their brain activity through neurofeedback training. Riccio et al. (29) evaluated a hybrid BCI system combining P300-based BCI with conventional assistive technologies, showing comparable usability to conventional assistive technology inputs, suggesting potential applications for cognitive training and communication support.

Recent Clinical Advances and Future Directions

BCI implementation in MS rehabilitation faces several distinct challenges. Buyukturkoglu et al.(30) identified fatigue as a significant factor affecting BCI performance, documenting specific EEG-derived functional connectivity patterns associated with MS-related fatigue. Their findings suggest the need for fatigue monitoring and adaptation mechanisms in future BCI systems. Disease progression variability presents additional complications for long-term BCI implementation. Shiels et al. (31) demonstrated that while MS patients achieved BCI control comparable to healthy controls, performance variability was higher, potentially due to disease-related fluctuations, indicating the need for adaptive BCI systems. Martinez-Cagigal et al. (32) developed an asynchronous P300-based BCI web browser achieving an average accuracy of 84.14% in MS patients, demonstrating feasibility for practical, daily-use applications despite disease-related limitations. However, fatigue management and system adaptability remain critical considerations for long-term use. Recent technological developments show promise in addressing these challenges. Chen et al. (33) demonstrated successful implementation of steady-state visual evoked potential (SSVEP)-based BCIs for assistive device control in MS patients, suggesting multiple BCI paradigms might accommodate different disease progression stages and symptom presentations. Future directions for BCI applications in MS rehabilitation include the development of hybrid systems combining multiple input modalities (26), integration of artificial intelligence for adaptive control (27), and implementation of fatigue management strategies (30). Additionally, the development of home-based BCI training systems, as demonstrated by Pinter et al. (28), may improve accessibility and facilitate more consistent therapeutic applications.

BRAIN-COMPUTER INTERFACE APPLICATIONS IN PARKINSON'S DISEASE REHABILITATION

Motor Rehabilitation

Addressing Motor Symptoms

Parkinson's disease (PD) manifests through a complex array of motor symptoms, including resting tremor, bradykinesia, rigidity, and postural instability, which significantly impact daily activities and quality of life (4). BCI technology has emerged as an intervention option for addressing these motor manifestations, offering both rehabilitative and assistive approaches for symptom management (34). Recent advances have led to the development of non-invasive and invasive BCI systems categorized into two approaches: rehabilitative BCIs aimed at promoting neuroplasticity and recovery, and assistive BCIs designed to provide direct control over external devices or stimulation parameters (5, 35).

Closed-loop BCIs for Adaptive Treatment

Closed-loop BCI systems, particularly in conjunction with deep brain stimulation (DBS), represent a significant advancement in PD treatment. These systems provide real-time feedback and adjust stimulation parameters based on ongoing neural activity and motor performance (36). Studies have demonstrated superior clinical outcomes compared to conventional approaches, with evidence showing better preservation of functional daily beta fluctuations and improved motor control (37). Machine learning algorithms have enhanced these systems' capability to identify patient-specific neural markers of motor performance. Castaño-Candamil et al. (38) demonstrated that supervised machine learning approaches can identify individual neural markers that are both sensitive to therapy and potentially useful as controllable variables in adaptive BCI systems.

Cognitive Rehabilitation

Executive Function and Memory Support

Beyond motor symptoms, cognitive decline represents a significant challenge in PD management. BCI-based cognitive training paradigms have shown promise in addressing executive function and memory deficits. Recent work combining BCI with virtual reality and artificial intelligence has demonstrated potential for enhancing adaptive responses and improving quality of life (13). Motor imagery-based BCI systems have shown particular promise in cognitive rehabilitation, improving both motor planning and execution through cognitive motor network engagement (39). This approach has demonstrated specific benefits for gait control, where motor imagery integration with BCI feedback can help patients overcome locomotor deficits.

Recent Clinical Advances and Future Directions

BCI implementation in PD rehabilitation continues to evolve with several significant developments. Rossi et al. (40) proposed integrating action observation treatment (AOT) with BCI-triggered muscle stimulation, suggesting potential enhancement of motor execution during rehabilitation sessions. Belkacem et al. (41) reviewed advanced closed-loop BCI systems incorporating various stimulation techniques (electric, magnetic, and optogenetic), demonstrating how feedback-based adaptation could improve therapeutic outcomes. Regarding signal acquisition and processing, Merk et al. (42) demonstrated electrocorticography (ECoG) superiority over subthalamic local field potentials for movement decoding in PD, with performance correlating to disease state. Their connectomic analysis approach showed potential for predicting individual channel performance across patients, supporting personalized BCI implementations. While Möller et al. (5) emphasize the need for additional research to establish feasibility, efficacy, and safety of technology-based neurorehabilitation in PD patients, key areas for future development include standardization of protocols across different disease stages, development of more user-friendly and accessible systems, integration of artificial intelligence for improved accuracy and adaptability, investigation of potential neuroprotective effects, and long-term studies to evaluate sustained benefits.

The field continues to advance, focusing on developing sophisticated closed-loop systems that adapt to individual patient needs and disease progression patterns. Recent advances in electrophysiological recording and analysis techniques, combined with machine learning approaches, suggest promising directions for BCI applications in PD rehabilitation (36).

Comparative Analysis of Brain-Computer Interface Applications in Stroke, MS, and PD

Efficacy Comparison

Brain-computer interface applications demonstrate varying levels of effectiveness across stroke, multiple sclerosis (MS), and Parkinson's disease (PD). In stroke rehabilitation, BCI systems present the most robust evidence base, with meta-analyses of nine randomized controlled trials (n = 235) showing a standardized mean difference of 0.79 in upper limb motor recovery compared to control interventions (10). MS studies demonstrate that patients can achieve BCI control comparable to healthy individuals (27, 31), though with higher performance variability due to disease-related fluctuations, with accuracy rates ranging from 84.14% to 93.18% depending on the paradigm used (29, 32). In PD, closed-loop BCI applications show particular promise, with adaptive systems demonstrating superior clinical outcomes compared to conventional approaches (37), including better preservation of functional daily beta fluctuations and improved motor control (36, 37).

Disease-Specific Challenges and Adaptations

Each condition presents unique challenges requiring specific BCI adaptations. Stroke rehabilitation requires BCIs to address lesion location heterogeneity and its impact on neural signal generation (9, 14). Studies show that both ipsilateral and contralateral motor areas may need targeted intervention depending on lesion location (8). MS systems must adapt to both disease progression and symptom fluctuation, with studies identifying specific EEG-derived functional connectivity patterns associated with fatigue(30). These systems require session-by-session calibration based on patient status (31). PD applications face challenges of dynamic symptom fluctuation and medication effects, necessitating sophisticated closed-loop systems that adjust stimulation parameters based on real-time neural activity (36, 37). These adaptive systems must account for both motor and non-motor symptoms, as demonstrated by variations in beta-band activity and movement decoding performance across medication states (42).

Patient Suitability and Customization

Patient characteristics significantly influence BCI effectiveness across all three conditions. For stroke, technical factors such as optimal processing time windows (1-2 seconds) affect system responsiveness and accuracy (17), while individual brain network connectivity patterns can predict therapeutic response (9). In MS, successful BCI implementation requires consideration of both fatigue levels and disease stage, with studies showing that neurofeedback training effectiveness correlates with specific changes in brain microstructure and functional connectivity (28). MRI studies reveal that successful BCI users show increased fractional anisotropy and enhanced connectivity within the salience and sensorimotor networks (28). In PD, movement decoding performance correlates with disease severity, with electrocorticography showing superior results compared to subthalamic recordings (42). The effectiveness of closed-loop systems varies with individual patient characteristics and disease progression (37), highlighting the need for personalized calibration approaches.

Promising Cross-Condition Findings

Several BCI approaches show promise across all three conditions, though with varying implementation requirements. Motor imagery protocols demonstrate effectiveness across conditions, achieving classification accuracies of 91.03% in stroke (16), comparable accuracies to healthy controls in MS (27), and successful integration with gait control in PD (39). Studies show that motor imagery activates similar motor areas across conditions (7), though with disease-specific variations in signal characteristics. Hybrid systems combining multiple signal types improve reliability across conditions, particularly when integrating EEG with EMG for continuous motion detection (18) or combining BCI with conventional assistive technologies(29). Recent advances in artificial intelligence and adaptive algorithms have enhanced system performance across all three conditions (15,43), suggesting a promising direction for future development.

Future Directions and Emerging Trends

Advancements in BCI Technology

Artificial Intelligence and Machine Learning Integration

Artificial intelligence is advancing BCI applications across neurological conditions. Machine learning algorithms improve signal classification accuracy and enable real-time adaptation to patient states (43). Recent developments in neural networks and advanced signal processing have achieved superior performance in decoding motor intentions, with classification accuracies exceeding 91% (16).

Hybrid BCIs

Emerging hybrid systems combine multiple neuroimaging and physiological monitoring approaches. The integration of EEG with EMG has demonstrated improved outcomes, enabling continuous motion detection and more natural interaction in rehabilitation settings (18). These multimodal approaches show improved reliability and broader application potential compared to single-modality systems.

Home-Based BCI Rehabilitation

The development of portable, user-friendly BCI systems enables home-based rehabilitation. Craik et al. (25) demonstrated the feasibility of low-cost, mobile EEG-based BCIs with high signal quality (SNR = 121 dB, CMRR = 110 dB) and reliability. Such systems could increase therapy intensity and accessibility, though they require careful consideration of remote monitoring and safety protocols.

Ethical Considerations and Quality of Life

The implementation of BCI technology requires addressing several key concerns. Access equity remains a significant challenge, with current systems often limited to specialized centers (15). Privacy and data security considerations become increasingly important as systems move to home settings. Long-term impacts on quality of life require systematic monitoring, particularly in progressive conditions like MS and PD.

Suggested Areas for Further Research

Several critical areas require additional investigation:

- Optimization of BCI protocols for cognitive rehabilitation across conditions, building on promising findings from both MS and stroke studies.
- Development of adaptive algorithms for disease progression in MS and PD, considering the dynamic nature of these conditions.
- Integration of BCI systems with existing rehabilitation protocols, focusing on complementary rather than replacement approaches.

• Standardization of outcome measures for cross-condition comparison, enabling more robust evaluation of intervention effectiveness.

• Long-term effectiveness studies in home-based settings, particularly important given the chronic nature of these conditions.

BCI technology in neurorehabilitation continues to advance toward increasingly sophisticated, personalized, and accessible systems. As highlighted by recent reviews (15), success depends on addressing both technical advances and practical implementation challenges. The field's evolution from technical achievements to patient-centered, home-deployable solutions represents a crucial step toward broader clinical adoption. Standardization of protocols and outcome measures remains essential for establishing evidence-based guidelines across conditions while maintaining flexibility for condition-specific adaptations.

CONCLUSION

Brain-computer interfaces have emerged as transformative tools in neurorehabilitation, demonstrating significant potential across stroke, multiple sclerosis, and Parkinson's disease treatment. The evidence presented in this review highlights both the remarkable progress in BCI technology and the distinct challenges that remain. Meta-analytic findings support BCIs' clinical efficacy, particularly in stroke rehabilitation, while emerging applications in MS and PD show promising results through adaptive and closed-loop systems. The integration of artificial intelligence, advanced signal processing, and hybrid approaches has substantially improved BCI performance and reliability. Classification accuracies exceeding 90% in motor imagery tasks and successful implementation of home-based systems demonstrate the technology's growing maturity. However, the field must address several critical challenges for widespread clinical adoption, including protocol standardization, accessibility, and long-term effectiveness evaluation.

Disease-specific adaptations have proven crucial for successful BCI implementation. Stroke rehabilitation benefits from targeted neural pathway activation, MS applications require fatigue management and adaptation to disease progression, and PD systems show promise through real-time symptom monitoring and stimulation adjustment. The development of portable, user-friendly systems represents a significant step toward broader therapeutic applications, though careful consideration of remote monitoring and safety protocols remains essential.

Future directions should focus on optimizing cognitive rehabilitation protocols, developing sophisticated adaptive algorithms for disease progression, and establishing standardized outcome measures for cross-condition comparison. The potential for home-based rehabilitation could significantly impact therapy intensity and accessibility, particularly benefiting patients with chronic conditions. As BCI technology continues to evolve, its role in neurorehabilitation will likely expand, offering increasingly personalized and effective treatment options for patients with neurological conditions.

Abbreviations

BCI - brain-computer interface
MS - multiple sclerosis
PD - Parkinson's disease
EEG - electroencephalography
MI - motor imagery
WHO - World Health Organization
EMG - electromyography
FES - functional electrical stimulation
VR - virtual reality
DBS - deep brain stimulation
ECOG - electrocorticography
SNR - signal-to-noise ratio
CMRR - common-mode rejection ratio
(f)MRI - (functional) magnetic resonance imaging

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Sažetak

INTERFEJSI MOZAK-RAČUNAR U NEUROREHABILITACIJI BOLESTI CENTRALNOG NERVNOG SISTEMA: PRIMENA KOD MOŽDANOG UDARA, MULTIPLE SKLEROZE I PARKINSONOVE BOLESTI

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Interfejsi mozak-računar predstavljaju inovativni pristup u neurorehabilitaciji neuroloških stanja, posebno moždanog udara, multiple skleroze i Parkinsonove bolesti. Ovaj rad pruža sveobuhvatnu analizu trenutnih primena interfejsa mozak-računar, tehnološkog razvoja i kliničkih ishoda kod ovih stanja. Nedavni napredak u sistemima zasnovanim na elektroencefalografiji pokazuje obećavajuće rezultate sa tačnošću klasifikacije preko 90% u rehabilitaciji nakon moždanog udara i uporedivim performansama kod pacijenata sa multiplom sklerozom i Parkinsonovom bolešću. Meta-analize studija rehabilitacije moždanog udara (n = 235) ukazuju na značajna poboljšanja motorne funkcije, sa standardizovanim razlikama od 0,79 u ocenama gornjih ekstremiteta u poređenju sa konvencionalnom terapijom. Specifični izazovi bolesti zahtevaju prilagođene pristupe, dok hibridni sistemi koji kombinuju više tipova signala i integraciju sa virtuelnom realnošću ili robotskom asistencijom pokazuju povećan terapeutski potencijal. Razvoj prenosivih sistema za kućnu upotrebu pruža mogućnosti za povećanje intenziteta terapije, istovremeno postavljajući pitanja o daljinskom praćenju i protokolima bezbednosti. Ovaj pregled sintetiše trenutne dokaze koji podržavaju primenu interfejsa mozak-računar u neurorehabilitaciji, istovremeno naglašavajući ključne oblasti za buduća istraživanja, uključujući optimizaciju kognitivne rehabilitacije i standardizaciju mera ishoda za poređenje između različitih stanja.

Ključne reči: interfejs mozak-računar, neurorehabilitacija, moždani udar, multipla skleroza, Parkinsonova bolest, motorna imaginacija, neuroplastičnost.

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