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Brain-Computer Interfaces in Post-Stroke Rehabilitation: A Narrative Review

Santosh Ramesh Achwani[1], Faique Tanvir Falke[2], Trishna Saikia Baruah[3], Rajkumar Krishnan Vasanthi[4], Abhijit Kalita[5], S Jayakumari[7], Tamalika Chakraborty[7], P Muthu Prasanna[8] and Abhijit Dutta[9]

[1]General Practitioner at Lismore Doctors, NSW, Australia; [2]Family Medicine Specialist, Burjeel Medical City, Abu Dhabi, UAE; [3]Faculty of Physiotherapy and Rehabilitation, Assam down town University, Panikhaiti, Guwahati, Assam, India; [4]Faculty of Health and Life Sciences, INTI International University, Nilai, Negeri Sembilan, Malaysia; [5]Faculty of Physiotherapy and Rehabilitation, Assam down town University, Guwahati, Assam, India; [6]Department of Anatomy, Sree Balaji Medical College and Hospi-tal. Chrompet. Chennai, India; [7]Department of Life Sciences, Guru Nanak Institute of Pharmaceutical Science and Technology, West Bengal, India; [8]Department of Pharmaceutical Biotechnolo-gy, Surya School of Pharmacy, Vikiravandi, Villupuram Dt. Tamil Nadu, India; [9]Royal School of Medical and Allied Sciences, The Assam Royal Global University Betkuchi, Guwahati, Assam, India

Correspondence:
Abhijit Dutta, PhD.
Royal School of Medical and Allied Sciences, The Assam Royal Global University Betkuchi, Guwahati, Assam, India.
E-mail: dutta.abhi2024@gmail.com

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ABSTRACT

Neurological illnesses, in particular, stroke, are a major cause of ailment and health risk around the world and often leave people with long-term disability. Stroke survivors often face problems with moving, thinking, and their mental health, which significantly reduces their quality of life. In the past, physical, occupational, and speech therapy were the main types of therapy used in rehabilitation for stroke. These methods use the brain's innate plasticity, i.e., its ability to reorganize and adapt after an injury, to bring back lost functions. Previous assessments of brain-computer interfaces (BCIs) for rehabilitation after a stroke have frequently failed in terms of clinical outcomes, long-term effectiveness, and/or with reintegration. Thus, it is imperative to review the therapeutic effectiveness, feasibility, and technological progress in BCI-based rehabilitation. This review focuses on recent trends in BCI stroke rehabilitation as well as BCI hybridization, recognizing the effect of emotions and stroke feedback on emotional status change. The review also focuses on clinical issues, existing constraints, and future possibilities related to improving motor and cognitive results. This study focuses on clinical applications, current stroke treatment issues, and new developments.

KEYWORDS brain-computer interface, stroke rehabilitation, neuroplasticity, and post-stroke

INTRODUCTION

Stroke is one of the most common causes of long-term disability (1). This disability makes it difficult to move, think, and be mentally healthy (2). Post-stroke rehabilitation helps the brain recover its normal functions by taking advantage of its natural plasticity, leading to changes in its structure and function in response to an experience or injury (3). For decades, physical therapy, occupational therapy, and speech therapy have been the main ways to help patients recover after a stroke (4). The efficacy of brain-computer interfaces (BCIs) varies considerably depending on stroke severity, lesion location, and individual patient characteristics (5, 6). Neurorehabilitation employs research on brain learning, adaptations, and changes based on experience to aid recovery from a stroke (7). Motor impairment is the most prevalent post-stroke deficit, significantly hindering patients' ability to perform daily activities and engage socially. Although spontaneous recovery often occurs within the first three months,

outcomes vary widely—particularly in individuals with severe impairments who typically experience slower and less complete recovery (8). Different types of rehabilitation training, such as task-specific training and constrained-induced motor training, have been used to assist stroke survivors with their motor abilities (9). BCIs stand for systems that record brain activity and turn it into computer commands that control equipment outside of the body. Some examples of these gadgets are communication devices (10), functional electrical stimulation (FES), and exoskeleton robots. Invasive BCIs can gather spatiotemporal signals and learn more about patients' needs through implants in the cerebral cortex (11). However, noninvasive BCIs that use signals from electroencephalography (EEG), magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), or functional magnetic resonance imaging (fMRI) may be more promising because they are safer and more ethical (12). The EEG signal-based BCI is the most common method since it does not require expensive or complicated gear. BCIs capture detailed neurophysiological data, including frequency-domain features (e.g., power in specific frequency bands) and temporal markers such as visually evoked potentials, P300, and slow cortical potentials. This neural information can be translated into control signals for external device manipulation (13). It can be simpler to control things outside of the body organically using hybrid BCI systems that employing more than one signal (14).

Motor imagery (MI) is a new approach to help with rehabilitation at all stages of stroke recovery (15). It involves mentally practicing real movement actions. Unlike active motor training (AMT), MI does not depend on any remaining motor function. Direct recordings of monkey brain cells have shown that the primary motor cortex is active during MI (16). A study of functional imaging in people who had a subcortical stroke found that their motor system was still active during MI, even when there were brain lesions (17, 18). BCI connects the brain to an outside device by responding to neural activity in the brain. This link does not employ the conventional neuromuscular pathways. BCI technology offers substantial benefits for individuals with neurological disorders, such as advanced amyotrophic lateral sclerosis, by enhancing communication and interaction capabilities. BCIs promote motor recovery post-stroke or traumatic brain injury by decoding brain activity and facilitating activity-dependent neuroplasticity (19). This technology can also help those who have difficulty in controlling their muscles or make a rehabilitation plan function better to help the patient achieve improved muscle control.

BCI FOR RECOVERING FROM A STROKE

BCI enables brain communications directly with an outside device, so there is no need for normal motor output pathways. BCIs can detect motor intention in stroke survivors, even in cases of paralysis, and convert these signals into actionable outputs such as activating robotic limbs or FES devices (20). One of the key ways that BCIs are expected to help people get well is by making the brain circuits that control movement stronger (21). BCIs can make the connection between motor intention and motor execution stronger by offering patients real-time feedback based on their brain activity. This helps the brain change and grow naturally. More research is underway about brain plasticity, neural regeneration, and rehabilitation therapy. Often BCI devices can read electrophysiological signals to determine the patient's need and then provide them feedback.

Stroke patients who utilize BCI-based therapy can have increased upper limb function, walking speed, and general capacity for independent life (22). Also, BCI treatments have been connected to changes in brain activity patterns, which suggests that they can change and normalize neural circuits involved in controlling movement. BCIs have significant potential, but it's always hard to use new technology in real-life clinical settings, and BCIs are no exception (23). BCIs function as real-time closed-loop systems, enabling users to interact with external devices and facilitating the acquisition of new motor skills through neuro feedback. A critical issue with BCI research is building systems that are robust and reliable enough to read brain activity in real life.

Buch et al. were the first to do a clinical study on using BCI with stroke patients (24). Eight people in that study used a MEG-based BCI to adjust the patient's mu rhythm so they could move a screen pointer. Six out of eight patients were able to use

the computer cursor that was attached to an orthosis on the stroke-injured hand. The Medical Research Council (MRC) assessment, on the other hand, did not indicate any big differences in motor results. Daly et al. reported about BCI effect in the real world for both MI and motor execution (ME), using FES feedback on one stroke patient (25). The patient was getting better, and could stretch their fingers effectively. Ang et al. offered an update on the findings of the randomized controlled trial (RCT) that were previously reported on 11 and 14 stroke patients (26). Broetz et al. described a case study in which they used EEG and MEG-based BCI with visual and orthosis feedback that was focused on daily living combined with physical therapy (PT) of one stroke patient (27). Prasad et al. also reported on five stroke patients who received MI BCI therapy and physical therapy at the same time (28). They employed the Action Research Arm Test (ARAT) and grip strength (GS) to evaluate the results which showed improvement in at least one of the tests. Ang et al. demonstrated that brain signals could be found in a sample of 54 stroke patients who utilized EEG-based BCI to undertake MI of the upper limb (29). That study indicated that most stroke patients used EEG-based MI BCI. Caria et al. reported on a stroke patient who received both EEG and MEG-based BCI therapy as well as physical therapy. They employed diffusion tensor imaging (DTI) and fMRI to demonstrate that the patient's brain could mend itself (30). These results affirm that BCI feedback is important and helpful in BCI stroke rehabilitation. There have been more trials of methods used with healthy people than on stroke patients which indicate BCI technology could benefit people with neurological diseases or give stroke sufferers back control of their motor abilities.

CLINICAL, ETHICAL, AND TECHNOLOGICAL IMPERATIVES

Future research is needed to optimize BCI protocols and identify individual predictors of therapeutic response, enabling more personalized neurorehabilitation. As the technology matures, BCIs are poised to play an important role in stroke and neurological recovery (31). EEG data provides sensitive information, thus secure transmission and privacy-preserving machine learning are critical (32). Despite recent advances, significant technical challenges persist, including brain signal modeling, modulation, processing, and detection (33). The primary goal remains the development of accessible, high-performing systems that enhance autonomy and quality of life for individuals with disabilities (34). BCIs now enable control of external devices such as computers, wheelchairs, robotic limbs, and exoskeletons via brain activity. However, the lack of long-term clinical outcome data limits widespread clinical adoption. Continued investigation is needed to optimize BCI applications in stroke recovery while addressing ethical concerns, including implications for autonomy, cognitive enhancement, coercion, mental privacy, and unintended consequences (35). Outcome measures should extend beyond motor recovery to encompass cognitive function, quality of life, and cost-effectiveness in resource-constrained healthcare settings. Promising directions include hybrid BCI systems that integrate multiple neural pathways to improve control accuracy and user feedback. Advances in non-invasive neuroimaging—such as high-density EEG and fNIRS—offer enhanced spatial and temporal resolution for capturing brain activity. BCIs interface with the central nervous system to translate sensory input and motor output into meaningful external interactions (36). BCI systems establish a direct interface between brain and external devices, bypassing traditional neuromuscular pathways (37). Active BCIs decode voluntary brain activity to enable user-driven control, while passive BCIs interpret cognitive or affective states without intentional input, supporting applications in neuroergonomics, neuromarketing, and adaptive automation (38). Reactive BCIs, by contrast, rely on brain responses to external stimuli, translating distinct neural reactions into corresponding commands. These systems, facilitated by advanced sensors and signal processing technologies, enable users, particularly those with motor impairments, to interact with their environment (39). The utility of BCIs spans assistive technologies, neurological rehabilitation, and gaming, though the efficacy of rehabilitation-oriented BCIs may depend on lesion size and location.

Stroke rehabilitation

When blood flow to the brain is interrupted, a stroke occurs—an acute neurological event that

damages neurons and leads to diverse motor, sensory, and cognitive impairments. The severity and type of disability depend on the location and extent of brain damage. Stroke remains a leading cause of long-term disability worldwide (40). A central objective of stroke therapy is to promote neuroplasticity—the brain's capacity to reorganize and form new neural connections, enabling healthy neurons to assume the functions of damaged ones. Rehabilitation commonly involves repetitive, task-specific training to strengthen neural pathways linked to motor and cognitive tasks. Many stroke survivors continue to face challenges in daily functioning and social reintegration despite intensive rehabilitation efforts (41). In order to enhance motor recovery and neuroplasticity, rehabilitation incorporates task-specific movement, repetition, and enriched environments. Studies also support the effectiveness of constraint-induced movement therapy in improving upper limb function. Canadian stroke guidelines highlight the potential of telerehabilitation and virtual reality (VR) as promising tools for chronic stroke recovery. VR-based interventions offer engaging, intensive practice tailored to optimize functional gains (42). Core therapies such as physical, occupational, and speech therapy aim to restore motor skills, balance, coordination, communication, and cognition. However, their efficacy may be limited in individuals with severe impairments, and access to specialized facilities remains a major barrier in many low-resource settings (43). Robotic-assisted therapy has emerged as a valuable adjunct, delivering high-intensity, repetitive training, particularly for upper limb rehabilitation. Younger patients tend to respond more favorably to neuroplasticity-based interventions (44).

Neuro rehabilitation via BCI

BCIs represent a promising innovation in stroke rehabilitation, offering potential for motor recovery and improved functional outcomes (45). By establishing a direct communication pathway between the brain and external devices such as computers or robotic limbs, BCIs harness neuroplasticity to reorganize neural networks and restore motor function. They are particularly beneficial for patients with severe motor deficits who struggle with conventional therapies, as BCIs allow bypassing of damaged neural pathways to facilitate device control. BCI systems can also be tailored to individual motor deficits, enabling personalized rehabilitation strategies. Standard BCI protocols involve signal acquisition, processing, feature extraction, and device control. During training, patients attempt specific motor tasks, such as grasping or wrist extension, while brain activity is recorded via EEG or other neuroimaging techniques (46). The system identifies movement-related neural patterns, which are then decoded into actionable commands through algorithmic translation, enabling external device control.

BCIs represent a transformative approach in neuro rehabilitation, particularly for post-stroke recovery (47). By establishing a direct link between the brain and external devices, BCIs enable users to control computers, robotic prosthetics, or assistive systems through neural activity. EEG is commonly used due to its affordability and ease of application (48). BCIs can also be categorized based on the neural signals they utilize—such as motor imagery, event-related potentials (ERPs), or steady-state evoked potentials. Passive BCIs, in contrast, monitor brain activity without user input, offering insights into mental or emotional states (49). The effectiveness of BCI-based rehabilitation depends on factors such as system type, training protocols, and the user's cognitive and physical capacity. In response to current challenges, ongoing research aims to enhance the reliability, accessibility, and usability of BCI systems for stroke recovery. BCIs can interpret users' intentions from brain states, with clinical applications (50). Motor imagery-based BCIs, for instance, translate imagined limb movements into control commands by activating motor planning areas in the brain. These signals can be harnessed to control external devices, potentially enhancing user performance with minimal conscious effort (51).

Brain neuroplasticity

Researchers have described neuroplasticity as the nervous system's ability to change shape in response to learning and stimulus (52). Changes in the strength of existing synapses or the creation of new synapses might cause the neuronal structures to reorganize. Researchers have found that motor recovery after a stroke involves a

number of alterations at the molecular, cellular, and physiological levels (53). In order to develop compensating circuits that let you get back the motor function lost, synapse-based learning rules need to be implemented. These processes are turned on when presynaptic and postsynaptic neurons fire at the same time. Long-term sensory inputs can cause depolarizing responses in the peri-infarct area, which can make those neurons more excitable. Using three types of stimulation—repetitive stimulation, paired stimulation, and closed-loop stimulation—these alterations in synaptic connection can be forced (54). Rehabilitation models that focus on creating activity-dependent plasticity can help people get well over the long run. For stroke victims to regain their motor function, the disrupted networks that control motor tasks need to be reconfigured.

Affective computing in BCI-based rehabilitation

The addition of emotion detection into BCI systems can enhance user engagement and motivation during rehabilitation by allowing devices to adapt feedback and training protocols based on the user's emotional state (55). Integrating BCIs with virtual reality further enriches the training environment, providing immersive, interactive experiences that promote adherence and sustained participation (56). BCIs can also detect mind-wandering, when attention drifts from the task, enabling real-time correction to maintain focus. Recent findings suggest that physical practice may be more effective than motor imagery alone in promoting motor recovery (57). Combining BCIs with adjunct therapies like transcranial magnetic stimulation (TMS) may further enhance neuroplasticity and expedite recovery. EEG-based BCIs support neurofeedback training, enable individuals to modulate emotional states by consciously altering brain activity (58). For instance, pre-stimulus theta and alpha wave activity has been linked to improved memory encoding. Neurofeedback training involves the voluntary regulation of brain activity. Post-stroke impairments are often associated with cortical hypoactivity and abnormal rhythms in the affected hemisphere, contributing to motor and cognitive deficits. Neuro feedback targets these dysregulated patterns, aiming to restore activity to more normative levels to facilitate recovery. Sensorimotor rhythm-based BCI training, including modulation of mu rhythms, has been investigated as an adjunctive approach for improving upper-limb motor function after stroke (59). Repeated neurofeedback sessions can produce long-lasting changes in neural activation, correlating with functional improvements. In most BCI-based motor rehabilitation paradigms, correct motor imagery or attempted movement triggers robotic or electrical-assisted motion of the affected limb, while failure results in movement absence. However, identifying optimal cortical targets for training remains a critical challenge, as the efficacy of neurofeedback and operant conditioning heavily depends on precise targeting.

Rationale for BCI in post-stroke rehabilitation

Neuroplasticity and the brain's capacity for cortical reorganization following neurological injury underpin the use of BCIs in post-stroke rehabilitation. Stroke-induced damage often disrupts motor pathways, resulting in impaired voluntary movement, typically affecting one side of the body. Robotic manipulators, beyond surgical applications, are increasingly integrated with BCIs and visual guidance systems to enable cooperative control in autonomous robotic grasping (60). BCIs harness the brain's adaptive potential, facilitating motor recovery through targeted neural feedback and reinforcement. The integration of artificial intelligence (AI) with BCIs enhances diagnostic accuracy, enables personalized treatment planning, and improves patient outcomes (61). BCI devices provide real-time neurofeedback by decoding motor intent from brain activity, promoting active patient participation in training and aiding neural circuit reorganization. Repetitive practice with feedback strengthens the link between intention and execution, leading to improved motor control. BCIs also show promise in addressing post-stroke cognitive impairments, including aphasia and attentional deficits. Passive BCIs adapt interfaces based on physiological signals without requiring conscious input, enhancing rehabilitation potential (62). When combined with neuromodulation, biofeedback, robotics, and wearables, BCIs can augment standard therapies to significantly improve functional recovery. Their adaptability allows for personalized rehabilita-

tion strategies tailored to individual deficits and capacities. Moreover, AI-assisted BCI systems may support personalized rehabilitation by improving neural signal decoding, adaptive feedback, and treatment customization according to individual motor and cognitive profiles. These tools offer scalable, customized mental health support through chatbots and virtual assistants, improving accessibility and responsiveness (63). The integration of clinical expertise with AI and clinical informatics is yielding promising outcomes, with the overarching aim of embedding AI-based mental health interventions into mainstream healthcare to ensure equitable, high-quality care for all youth.

Current state of BCI in stroke recovery

Researchers and developers are still working on BCI technology for post-stroke rehabilitation to make these treatments more effective, easier to use, and easier to access. A lot of AI technologies have been used in health care settings, such as AI chatbots, different language models, prediction modeling, sentiment analysis, and recommender systems (64). AI-powered technologies are revolutionizing mental health care by improving diagnoses, personalized treatment, and tailored services. Researchers are testing various BCI paradigms, such as motor imagery-based, sensorimotor rhythm-based, and event-related potential-based BCIs, to help people recover motor function after a stroke. AI applications, such as chatbots and games, keep teens engaged and provide ongoing support. Combining BCI systems with other rehabilitation methods, such as robotic therapy and virtual reality, can lead to synergistic results. These new methods could help stroke survivors recover more completely and improve their quality of life overall (65). Researchers have been able to expand the possibilities of BCI beyond just medical uses for healthy people. They are also working on creating non-medical uses, such as generations of prototypes of hands-free products. Brain-computer interface technology for stroke rehabilitation could let a person's brain activity operate independent of devices or give feedback, with the goal of improving motor recovery and functional independence.

BCI-robot systems can improve fine motor abilities, but challenges remain, such as high costs and accessibility. Plans are underway to create cheaper, more portable devices for rehabilitation settings. Concerns about data security, privacy, long-term effectiveness, social and economic inequalities, and resistance from healthcare professionals need to be addressed. Additionally, BCI systems require extensive training, making them difficult for doctors without specialized training in neuro technology to use.

Stroke patients' unique responses to BCI therapy make it challenging to find effective treatment plans. Future research should focus on creating unique therapies which consider factors like lesion location, stroke severity, and cognitive function. Self-paced BCIs should be available which are controlled by brain signals. While not suitable for everyone, BCIs offer new treatments for mental illnesses like depression and anxiety. There have been some good results with BCI for upper extremity rehabilitation, but there aren't as many trials using BCI for lower extremity rehabilitation (66). This could be because moving the lower extremities is more complicated and allows for a lot of freedom. Additionally, it can be hard to pick up on brain signals that are related to moving the lower body because of noise from muscle activity and body movement.

Hybrid and multimodal BCI approaches

If BCI were combined with other technologies, such virtual reality or robots, it could lead to more complete and effective rehabilitation programs. Somatosensory feedback to BCI systems can give people a sensation of touch and proprioception, which can help them be more aware of their movements and improve their motor control (67). People with acquired brain injuries have been assisted to adapt by using multisensory stimulation. This method takes advantage of the best parts of both styles. Virtual reality may provide training environments that are realistic and immersive, while robotics can help with movement and make it easier to master motor skills. Purposeful, repetitive, and high-intensity practice significantly enhances motor skill acquisition. Therapists may restrict the use of the less-affected limb to promote greater use of the impaired one, while also providing feedback to reinforce task performance and encourage progress (68). The rehabilitation environment, the gadgets used, and the personalized procedures used are a few of the many fac-

tors that can affect the success of rehabilitation. Therapists now are using robotic devices more often to help them offer tailored treatments and keep track of their patients' improvement. Robotic systems can help with neuroplasticity and motor outcomes by providing high-repetition, task-specific training. When BCI is combined with robotic systems, it can become a closed-loop rehabilitation system.

Noninvasive BCIs

Noninvasive BCIs do not need to be surgically implanted, and they can detect brain impulses from the outer side of the scalp. Slow cortical potentials are measurements of cortical polarization that can be recorded from any part of the scalp, but the front central region is best, over a period of 0.5-10.0 s. People who use BCIs that measure slow cortical potentials learn to choose options on a screen by adjusting the amplitudes of the slow cortical potentials to move a cursor and choose letters (69). Sensorimotor rhythms are sinusoidal frequencies in the alpha range (8–13 Hz) that can be found in the motor and somatosensory cortex. Patients using BCIs that measure sensorimotor rhythms learn how to choose options on a screen by moving a cursor and choosing letters with their sensorimotor rhythms (70). The P300 evoked brain potential in about 300 ms following a fresh, unexpected stimulus which can be seen in an EEG. The signal has a positive electrical charge and gets stronger when the stimulus receives more attention. The user focuses on the letter they want, and when it lights up, a P300 ERP is sent out that tells them to choose that letter (71). BCIs that detect steady-state visual evoked potentials (SSVEPs) capture EEG signals from the occipital cortex, affecting attention and vision in individuals with severe neurological diseases. Error-related negative evoked brain potentials occur 200-250 milliseconds after incorrect responses, stopping reward stimulus. fMRI, based on blood oxygen levels, can show changes in brain metabolic activity and neural activity. However, emotional responses were not significantly modulated following training (72).

Invasive BCIs

Invasive BCIs involve implanting electrodes into the brain to record neural activity and enable users to control external devices through decoded neural signals (73). However, results have been less promising in patients with completely locked-in syndrome (CLIS) due to amyotrophic lateral sclerosis (ALS). In these cases, placing electrocorticography (ECoG) electrodes on the cortical surface failed to produce meaningful outcomes (74). Given the limited sample size and variable results, current data on invasive BCI use in ALS, particularly in CLIS remain inconclusive, warranting further investigation to establish efficacy and long-term reliability.

Upper limb rehabilitation via BCI

Two-thirds of those who survive a stroke have chronic upper limb paresis, and half of them have severe paresis (75). Because traditional methods have their limits, new technological alternatives like BCIs, which use robotic systems and electrodes to stimulate the neural system, can make stroke rehabilitation more effective. Effective upper-limb rehabilitation after stroke emphasizes repetitive, task-specific, and intensive practice (76). Using BCI for rehabilitation can help improve motor function in the upper body after a stroke by increasing brain activity and encouraging neural plasticity. Biological methods for repairing neurons can make post-stroke rehabilitation better. Some studies on upper limb rehabilitation using BCI have used non-invasive brain stimulation (NIBS) as an extra treatment. NIBS, which can be given as transcranial magnetic stimulation or transcranial direct current stimulation (tDCS), is usually given right before a BCI rehabilitation session to change the state of cortical activity (77). In stroke patients, excitatory NIBS stimulation is usually delivered to the ipsilesional motor cortex (M1) and inhibitory NIBS stimulation is applied to the contralesional M1 and is done to target the diminished ipsilesional M1 activations and enhanced inter-hemispheric inhibition. Some people have believed that the brain's facilitatory state after NIBS may have a priming effect that makes the next BCI therapy work better. Before employing NIBS to block the contralesional hemisphere, it is important to completely grasp the contralesional hemisphere in the post-stroke condition. The contralesional hemisphere becomes more active after a stroke and this greater activation leads to a stronger inhibitory drive on the damaged hemispheres.

Lower limb rehabilitation via BCI

BCI-based therapy improves lower limb motor function in stroke survivors by enhancing gait and balance, crucial for post-stroke recovery and independent mobility. It enhances neuroplasticity and promotes functional gains through task-specific, repetitive training and cortical activation. Tele rehabilitation further enhances accessibility to therapy, offering a cost-effective and scalable alternative through remote consultations, virtual environments, and home-based therapeutic devices. Early implementation, both in-hospital and at home, has been proven feasible and safe (78). Robotic-assisted rehabilitation, including BCI-integrated systems, has demonstrated significant potential in both research and clinical settings. Chung et al. reported significant improvements in timed up-and-go (TUG), cadence, and step length following five sessions of BCI-FES compared with FES alone (79). Similarly, BCI-based neuro feedback has led to greater gains in gait parameters compared to random-feedback controls. Despite encouraging outcomes, challenges remain, particularly electromyographic (EMG) contamination and the complex neural control of gait involving cortical and subcortical networks, which must be addressed to advance clinical translation.

Cognitive training

Cognitive impairments following stroke encompass deficits in attention, information processing speed, memory, semantic fluency, and language production, including aphasia (80). As language functions are critical in complex cognitive processes such as reasoning and abstraction, their disruption significantly impairs overall cognition. Effective participation in therapies, including BCI-based motor rehabilitation, requires a minimum level of cognitive functioning to comprehend and engage with task demands. BCI-based functional electrical stimulation has also been investigated to improve balance and gait-related outcomes in patients with stroke (81).

Cognitive impairment is a common consequence of stroke and may affect attention, memory, executive function, and other domains relevant to rehabilitation (82). Targeted modulation of cortical regions through self-regulation techniques may offer a promising avenue for cognitive rehabilitation. Meta-analyses and neuroimaging studies support the efficacy of neurofeedback in enhancing cognitive performance. Given the heterogeneous nature of post-stroke cognitive deficits, tailoring BCI-based interventions to specific impairments is critical for optimizing recovery (Figure 1).

Neuronal damage caused by stroke commonly leads to a spectrum of motor, cognitive, and affective impairments. While each of these deficits can independently hinder recovery, they also exert mutual influence, often complicating rehabilitation efforts. Improvement in one domain may positively impact others. BCI-based robotic systems have also been investigated for wrist and hand rehabilitation, with randomized trials demonstrating their potential to support motor recovery after chronic stroke (83). Similarly, engaging in aerobic exercise prior to cognitive rehabilitation has been shown to boost cerebral blood flow (CBF) and arousal, thereby priming the brain for improved cognitive performance. Affective symptoms, including depression and anxiety, significantly impair quality of life and rehabilitation outcomes. BCI-based attention training has also been investigated in neurodevelopmental disorders, including attention-deficit/hyperactivity disorder (ADHD), although such evidence cannot be directly extrapolated to post-stroke rehabilitation (84). Better motor rehabilitation is frequently associated with enhanced motivation and improved mood profiles. These interconnected findings highlight the need for a comprehensive, integrative rehabilitation strategy that leverages the synergy among motor, cognitive, and affective systems to maximize functional recovery as shown in Figure 1.

Emotion and mood regulation

Depression and anxiety, often under recognized during the rehabilitation process, can significantly hinder the translation of functional improvements into meaningful gains in quality of life. BCI-controlled functional electrical stimulation has also been investigated as a rehabilitation strategy for post-stroke shoulder subluxation (85). Depression can lead to a gap between perceived obligations and actual behavior, hindering rehabilitation efforts. This can exacerbate feelings of hopelessness in patients with severe post-

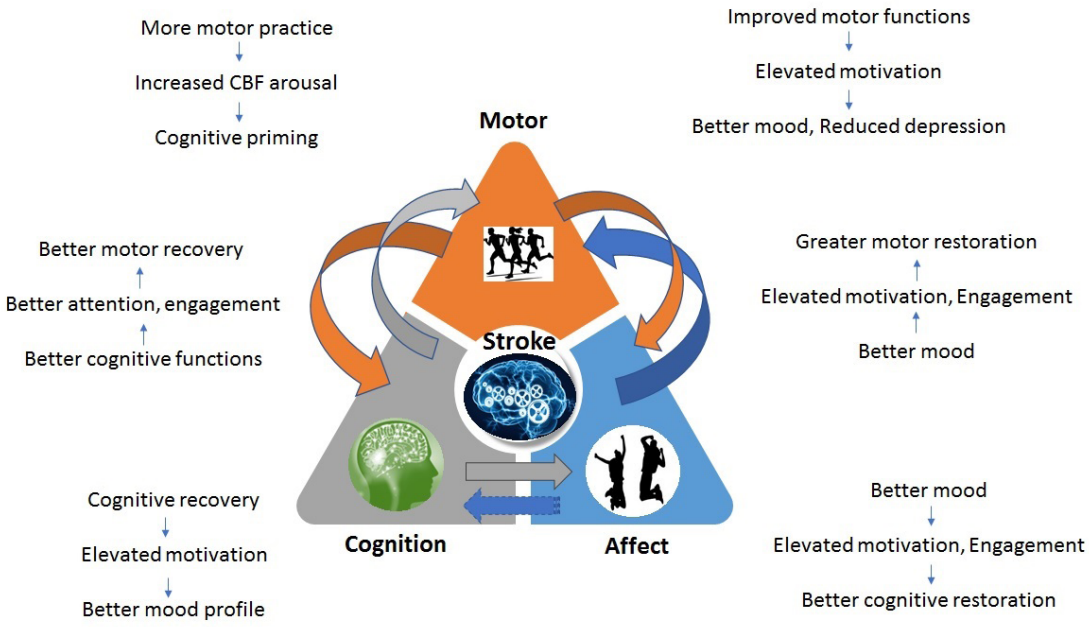


Figure 1. Post-stroke motor, cognitive, and affective deficits and their intricate interrelationships
CBF, cerebral blood flow

stroke disability. BCI-based stroke rehabilitation can help reengage patients demotivated by depression. Post-stroke depression is an important affective complication that may adversely affect participation, functional recovery, and quality of life after stroke (86). Concurrent EEG and fMRI studies have identified amygdala activation patterns linked to EEG biomarkers, offering promise for the development of EEG-based emotional regulation systems within BCI frameworks.

Considerations for clinical implementation

Clinical integration of BCI technology requires consideration of cost-effectiveness, usability, and accessibility. Larger, adequately powered clinical trials with longer follow-up are needed to establish the long-term efficacy and durability of BCI-based rehabilitation (87). However, the high cost of BCI systems presents a significant barrier, particularly in resource-constrained settings. This challenge may be able to be mitigated through the adoption of low-cost hardware and open-source platforms. Robotic-assisted systems can provide individualized and repeatable training and may facilitate objective monitoring of rehabilitation progress. AI-driven digital therapeutics are especially valuable due to their scalability and low marginal cost.

AI integration with augmented reality (AR), VR, and Internet of Things (IoT) offers potential for healthcare applications. User-friendly, intuitive BCI systems are crucial for widespread adoption. AI enhances diagnostic accuracy, optimizes therapeutic strategies, and improves patient outcomes (88). With the expansion of digital infrastructure and the proliferation of robotic technologies, healthcare services have become increasingly accessible and user-centered. AI algorithms can analyze extensive datasets, including genomic information, to inform personalized treatment protocols (89). The advent of AI-enabled medical technologies has ushered in the era of augmented medicine, an approach wherein AI augments clinical decision-making and patient management (90). Ethical concerns surrounding data privacy, algorithmic transparency, and equitable deployment must be addressed through robust regulatory frameworks. Upholding ethical standards is essential to building public trust and ensuring the responsible development and deployment of AI in healthcare. The synergy among AI, robotics, and digital technologies continues to drive innovation across domains such as surgery, rehabilitation, and diagnostics (91). As AI advances, it is poised to transform healthcare delivery by equipping clinicians with enhanced decision-support tools and expanding modes of patient engagement (92).

Current challenges and future directions

Developing robust and reliable BCI systems for stroke rehabilitation presents several technical and clinical challenges. These include inter-individual variability in neural activity, the extensive training required for effective system use, and susceptibility to artifacts and noise interference. User acceptance is significantly influenced by system usability and comfort (93). Non-stationarity of brain signals, due to factors such as learning, fatigue, or emotional state, complicates long-term BCI performance. To address this, adaptive systems that incorporate real-time emotional or cognitive state monitoring have been proposed (94). Despite the broad potential of BCI technologies, associated risks, particularly those related to invasive approaches, must be carefully managed (95). Addressing these limitations necessitates the development of adaptive algorithms capable of accommodating neural variability and enhancing system stability and reliability. However, consensus is lacking regarding the optimal therapeutic strategy for individual patients; in many cases, treatment selection is constrained by the resources available at clinical facilities (96). The future of BCI-assisted stroke rehabilitation is promising, as ongoing research continues to refine these systems for greater usability, adaptability, and patient-specific customization. Noninvasive neuroimaging modalities such as fMRI, positron emission tomography (PET), TMS, EEG, and MEG have contributed to our understanding of motor system reorganization and opened new avenues for targeted rehabilitation interventions (97). Improved outcomes may be achieved by tailoring rehabilitation protocols to the patient's specific neurological profile, motor deficits, and cognitive capacity.

Neural interfaces offer insights into motor control and plasticity, but have limitations for complete functional motor restoration. Implantable electrodes offer high-resolution decoding, but clinical adoption is hindered by risks. Rehabilitation strategies should use preserved afferent pathways in stroke patients for neuroplastic adaptation and improved brain stimulation.

CONCLUSIONS

Brain-computer interfaces represent a promising adjunctive approach to post-stroke rehabilitation, particularly for individuals with persistent motor impairments who have limited benefit from conventional rehabilitation alone. Current evidence suggests that BCI-based interventions, including motor imagery, sensorimotor rhythm-based systems, neurofeedback, and hybrid BCI systems combined with functional electrical stimulation, robotics, or virtual reality, may improve motor and functional outcomes, especially in upper-limb rehabilitation. However, the available evidence remains heterogeneous, with substantial variability in BCI paradigms, training protocols, outcome measures, patient characteristics, and follow-up duration. Important limitations include small sample sizes, inter-individual variability in neural signals, signal noise and non-stationarity, intensive training requirements, high costs, limited long-term evidence, and challenges related to accessibility and clinical implementation. Invasive BCIs additionally involve surgical and device-related risks. Therefore, larger, well-designed randomized controlled trials with standardized protocols, clinically meaningful outcomes, longer follow-up, and individualized adaptive approaches are needed to establish the long-term effectiveness, safety, and clinical applicability of BCI-based post-stroke rehabilitation.

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to report.

AUTHOR CONTRIBUTIONS

S.R.A.: conceptualization, methodology, software, writing — review & editing; A.D.: data curation, writing — original draft; R.K.V., A.K.: visualization, investigation; F.T.F., T.S.B: supervision, project administration; S.J., T.C.: software, validation,

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All authors have read and agreed to the published version of the manuscript.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available within the article and its referenced sources. As this is a narrative review, no new datasets were generated or analyzed.

INSTITUTIONAL REVIEW BOARD STATEMENT

This review article does not report on new experimental research involving humans or animals; therefore, ethics approval was not required.

INFORMED CONSENT STATEMENT

This review article does not include research involving human participants; therefore, informed consent was not required.

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