Proceedings of ICBioMed 2025 Symposium: Computational Modelling and Simulation for Biology and Medicine
DOI: 10.54254/2753-8818/2025.LD25936

Brain-Computer Interface in the Treatment of Stroke

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Abstract. Stroke remains a leading cause of adult disability, leaving most survivors enduring persistent motor deficits. Traditional rehabilitation often yields some recovery initially, yet soon plateaus, especially in severely impaired patients. Brain–computer interfaces (BCIs) decode cortical signals (e.g., EEG, ECoG, fNIRS) with pattern-recognition algorithms to create closed-loop systems that deliver real-time feedback. Common paradigms include motor imagery or attempted-movement tasks, functional electrical stimulation (BCI-FES), robotic exoskeleton control and virtual-reality training. There is much evidence from randomized controlled trials and meta-analyses supporting BCI-based interventions' validity and effectiveness in both motor improvement and enhancing neuroplasticity compared to conventional therapy. Despite this potential, BCIs have usability problems (such as long calibration times and user fatigue). In addition, technical difficulties like noisy and nonstationary signals, limited bandwidth, complicated setup requirements, and ethical issues regarding both informed consent and data privacy do exist. Overcoming all the restrictions mentioned above and fulfilling the clinical potential of BCIs is the current ongoing goal. This review aims to synthesize current evidence, highlight key technological and clinical challenges, and propose strategic directions for translating BCIs into routine post-stroke rehabilitation.

Keywords: brain-computer interface, stroke rehabilitation, motor imagery, neuroscience

1. Introduction

Stroke puts a strong health burden worldwide, not only a leading cause of adult disability, but also remains one of the most common neurological conditions [1]. Survivors frequently contend with hemiparesis, spasticity, and impaired dexterity, conditions that erode autonomy and impose lifelong socioeconomic costs. In the United States alone, there are about 795,000 people who experience a stroke each year, and around 6.6 million stroke survivors are currently enduring its chronic consequences [2]. Though conventional rehabilitation does improve function after stroke, outcomes are often limited. Within the first few months following a stroke, there will be a rapid improvement in function, which will plateau after a year, with little progress after that. For the condition above, even with continued therapy, many survivors are unable to recover fully. Therefore, improving the quality of life for stroke survivors requires the development of more efficient post-stroke rehabilitation techniques.

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Traditional therapies, such as task-oriented physiotherapy, rely heavily on the patient's residual motor function after stroke and intensive therapist supervision. This process will have not only a limited effect for those patients with severe paralysis, but also place considerable demands on clinical resources. In addition to that, the growing number of patients challenges the scalability of this labour-intensive model. Recently, BCIs have emerged as a promising method that may take the place of conventional therapy. BCIs provide a mechanistically distinct avenue for restoring function. By translating cortical intent into control commands, BCIs circumvent damaged corticospinal pathways and re-engage latent neural circuits [3]. BCI systems do so by recording neural activity and decoding the user's moving intention, then translating that intent and sending it to control commands for external devices (such as robotic orthoses and a computer cursor) [4]. Notably, a BCI may generate movement without any residual muscular activity. Given that the decoded commands are independent of real limb movement, stroke survivors who are completely paralyzed can still regulate their brain signals to control a BCI [5].

By providing real-time and closed-loop feedback (e.g. a patient imagines a movement and sees a device execute it), BCIs allow active training that engages the brain's plasticity. This kind of patient participation is needed for learning or regaining motor skills, which will help to reinforce activity-dependent neuroplastic changes in remaining neural circuits. Furthermore, BCIs can be implemented noninvasively, like EEG, or through implanted devices. For example, a recent first human trial of a fully implanted endovascular BCI demonstrated that patients with chronic paralysis could safely control digital devices "by thought," using a stent-like recording implant in the motor cortex [6]. These developments suggest a new paradigm in neurorehabilitation by underlining the special ability of BCIs to help people with severe impairments regain movement and communication.

Even with these developments, routine adoption remains hindered by several challenges. Long-term device safety, user agency, and data privacy must all be covered by ethical and regulatory frameworks. Against this backdrop, the present review provides a comprehensive appraisal of BCI-enabled stroke rehabilitation. Future direction will also be included, especially on how to translate BCIs into routine stroke rehabilitation. By carefully evaluating these new neurotechnology-driven treatments, we aim to better understand their contribution to stroke recovery and how they can assist in meeting the urgent demand for more efficient rehabilitation solutions.

2. Principles and system architecture of BCI

2.1. Signal acquisition modalities

Neural signals for BCI can be acquired by several modalities. The most common noninvasive method is scalp EEG, which is relatively cheap and portable with excellent millisecond temporal resolution but relatively coarse (in cm-scale) spatial resolution. Subdural electrocorticography (ECoG) is semi-invasive and has much higher spatial (~mm) and bandwidth resolution (up to kHz), and is less prone to muscle artifacts, but it requires neurosurgical implantation. Functional near-infrared spectroscopy (fNIRS) is another noninvasive option, using optical sensors to measure cortical hemodynamic (oxyhemoglobin) signals. fNIRS offers better spatial localization than EEG, but at the expense of very low temporal resolution (on the scale of seconds). In sum, EEG is most widely used for stroke-BCI because it is safe and portable, whereas ECoG and fNIRS trade invasiveness or latency for higher spatial accuracy [7].

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2.2. Data preprocessing and feature extraction

Raw EEG/ECoG signals are typically band-pass filtered to the frequencies of interest (e.g. 8–30 Hz for motor imagery) and notch filtered to remove line noise. Artifact removal is critical: algorithms like independent component analysis (ICA) are commonly applied to separate and remove eye-blink or muscle artifacts. After denoising, movement-related features are extracted. In motor tasks, event-related desynchronization/synchronization (ERD/ERS) of sensorimotor rhythms is a key signature. For example, imagined or attempted limb movements produce a transient power decrease in the mu (8-13 Hz) and beta (13-30 Hz) bands over contralateral motor cortex [8]. Spatial filters like Common Spatial Patterns (CSP) and its variants are widely used to maximize the variance difference between “move” and “rest” conditions. For instance, CSP computes channel weights that maximize band power for one class and minimize it for the other [9]. In practice, filter-bank CSP (FBCSP) or regularized CSP methods are often used to capture subject-specific frequency bands.

2.3. Decoding algorithms

After feature extraction, the low-dimensional feature vectors are classified in real time. Linear discriminant analysis (LDA) mostly remains a workhorse for BCI due to its computational efficiency and robustness. Linear support vector machines (SVMs) are also widely used, which construct separating hyperplanes and inherently maximize the margin between classes. In addition, Nonlinear kernels (e.g. Gaussian/RBF) in SVM can improve accuracy for complex EEG patterns. More recently, deep learning models have achieved high accuracy. Convolutional neural networks (CNNs) can learn spatial–spectral patterns from raw or time-frequency EEG images. For example, 1D/2D CNNs have been shown to decode motor imagery and SSVEP signals with accuracies often above 80–90%. Recurrent neural networks (RNNs) such as LSTM architectures capture temporal dependencies in EEG time series and have been applied to sleep staging and Motor imagery (MI) decoding. In summary, common classifiers in stroke-BCI include LDA and SVM for speed and small data, and deep models (CNN/RNN or hybrids) for potentially higher accuracy when large training sets are available [9].

2.4. Real-time system architecture

A closed-loop BCI comprises an EEG amplifier or headset, signal pipeline, and feedback device. In hardware, electrodes (both wet and dry) are mounted on a cap wire, the scalp to a low-noise amplifier and ADC (often 16-64 channels, 24-bit resolution). For example, one system uses a 16-channel g.USBamp (24-bit ADC) sampling at 256 Hz (0.1-100 Hz bandpass) [10]. Wireless, battery-powered headsets (e.g. Emotiv, g.NAUTILUS) and compact amplifiers now exist for mobility. The digitized EEG is streamed to a real-time processing unit (embedded DSP or PC) running software (e.g. BCI2000, OpenViBE). Here, the signal is filtered, cleaned (ICA, regression), and features are computed continuously. The classifier then outputs commands (e.g. “left” vs. “right” motor intent) which drive actuators. Finally, sensory feedback (visual display, robotic movement, electrical stimulation) is delivered to the user to complete the closed loop. This real-time pipeline operates with minimal latency (tens of ms) so that user intentions are immediately reinforced by the feedback. Overall, the choice of hardware and software architecture balances cost, portability, and performance; EEG-based BCIs are favoured in stroke rehab for being safe, adaptable, and fast enough for real-time feedback [11].

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3. BCI-driven rehabilitation paradigms

3.1. Motor imagery-based training

MI is a cornerstone of stroke BCI rehabilitation. During MI, the patient imagines moving a paretic limb, which elicits “movement-related” EEG signatures without actual motion. Specifically, attempted or imagined movement generates movement-related cortical potentials (MRCPs) and sensorimotor ERD/ERS patterns. MRCPs are slow cortical potentials that precede movement intention, while ERD/ERS appear as a decrease or increase in mu-beta power over sensorimotor cortex during and after the imagined movement [8]. Importantly, MI can activate similar cortical networks as actual movement, so training MI fosters neuroplasticity even when the limb is weak. BCIs detect these patterns in real time to infer the patient’s motor intention. Studies consistently show that MI-BCI training with feedback improves motor outcomes more than training alone. In practice, the patient performs repeated MI tasks while the BCI decodes their “intent” and provides feedback only upon correct detection. Randomized controlled trials have demonstrated that only the group with MI-contingent feedback gained significant hand strength and range of motion [12].

3.2. BCI-integrated functional electrical stimulation (BCI-FES)

Combining MI detection with functional electrical stimulation (FES) bridges the gap between cortical intent and peripheral execution. Real-time FES pulses are sent to the corresponding limb muscles (such as the flexors or extensors of the wrist or finger) when the BCI classifier detects the desired movement. The FES is given based on the neuronal intent, usually within hundreds of milliseconds of the MI beginning. This precise coupling (brain intent to muscle contraction) reinforces Hebbian plasticity along the motor pathway. Typical BCI-FES systems target affected muscles via surface electrodes: for example, electrodes over the finger extensor and flexor muscle groups are stimulated to produce hand opening/grasping contractions. Stimulation parameters (pulse width, frequency, and amplitude) are adjusted to elicit visible movement without discomfort. Meta-analysis indicates that stroke-BCI studies incorporating FES feedback achieve larger motor gains (Hedges’ $g \approx 1.2$) than modalities relying on visual feedback alone [10]. In chronic stroke, BCI-FES has yielded lasting improvements in arm function [13]. Nevertheless, optimal FES timing and dosage remain active research topics.

3.3. Robotic and orthotic assistance

BCI-controlled robotics provides active support for movements that patients cannot perform voluntarily. For upper limb rehab, wearable robots or exoskeletons can move the patient’s arm or hand in concert with their intention. For example, EEG-based MI commands have been used to control the MIT-Manus robotic arm to assist reaching, as well as soft robotic gloves for hand grasp. In a typical scheme, when the BCI detects an “open hand” or “extended elbow” intent, the robot’s actuators drive the limb through that motion. This support allows paretic patients to experience movement they cannot voluntarily do and closes the sensorimotor loop. Other designs use hand orthoses or powered exoskeletons under BCI control. In all cases, the BCI makes robotic therapy active: the device only assists when the patient generates the correct brain signal. Clinical studies show that BCI-robotic systems can improve range of motion and function, which is likely done by combining repetitive practice with neural feedback [12].

DOI: 10.54254/2753-8818/2025.LD25936

3.4. Closed-loop sensory feedback

Closed-loop feedback is essential for reinforcing the association between intention and outcome. Most MI-BCI systems include continuous visual feedback: for instance, a moving cursor or virtual limb that follows the user's control signal. Immersive virtual reality (VR) or augmented reality (AR) can enrich this loop by presenting a realistic limb movement or game-like environment when MI is successful. Visual feedback (e.g. seeing a virtual hand grasp an object) engages sensorimotor areas and provides explicit performance cues. Beyond vision, some systems add proprioceptive cues (e.g. tongue stimulation) to further inform the brain. Critically, closed-loop feedback, delivered only upon detection of correct brain patterns, will strengthen the association between intention and outcome. Neurophysiologically, this bidirectional feedback promotes Hebbian plasticity: users learn to modulate their brain rhythms when they see the robot move or feel a stimulation in response. Studies indicate that multimodal feedback (visual + somatosensory) accelerates recovery by continually closing the loop between motor intent and sensory consequence [11].

4. Clinical trials and outcome evaluations

4.1. Common measuring scale

Stroke-BCI studies usually assess motor recovery using standard clinical scales. Common measures include the Fugl-Meyer Assessment of Motor Recovery (FMA, especially upper-extremity subscore, range 0-66) for sensorimotor impairment, the Action Research Arm Test (ARAT) for arm function, and the Barthel Index (BI) for activities of daily living. These scales quantify improvements in strength, coordination, and daily function. In stroke BCI trials, most studies report gains on FMA-UE and ARAT, and some include Barthel or Modified Barthel as a measure of independence. For example, Li et al. (2025) note that FMA, ARAT and Barthel Index were primary outcomes in the trials they reviewed [13].

Pooled analyses of randomised controlled trials find that EEG-based BCI training outperforms conventional therapy. Mansour et al. pooled 12 RCTs (298 patients) and found a large short-term effect on upper-limb function (Hedges' $g \approx 0.73$) favouring BCI, and a moderate long-term effect ($g \approx 0.33$) [8]. Similarly, Zhang et al. (2022) meta-analysis (13 RCTs, $n \approx 258$) reported a moderate standardized mean difference (SMD≈0.56) in FMA-UE favouring BCI [14]. A more extensive meta-analysis (21 RCTs, $n \approx 886$) confirmed that BCI training significantly improved FMA-UE by a mean difference of ~3.7 points compared to controls, and also showed significant gains on the Wolf Motor Function Test and ARAT. Meta-analyses of BCI combined with functional electrical stimulation (FES) likewise show moderate benefits: Ren et al. reported SMD≈0.50 for BCI-FES versus FES alone [15]. Notably, subgroup analyses suggest that richer feedback (e.g. contingent FES or robot-assisted movement) and intention-based paradigms yield larger gains [16].

4.2. Key randomized controlled trials

Representative RCTs mirror these meta-analytic findings. A ReHand-BCI RCT randomized 30 chronic stroke patients to 30 sessions of an EEG-BCI controlling a hand exoskeleton versus a sham-BCI control. Both groups improved on FMA-UE, but only the BCI group showed significant ARAT gains. The BCI group also trended toward greater ipsilesional cortical activation (EEG and fMRI) and corticospinal integrity, suggesting neuroplastic change. In Seo et al., double-blind trial, chronic stroke patients receiving motor-imagery BCI with FES feedback (recoveriX system) showed

DOI: 10.54254/2753-8818/2025.LD25936

significantly greater wrist extensor strength (MRC scale) and range of motion than sham-BCI controls, and these gains correlated with increased functional connectivity in the injured hemisphere. Taken together, these trials support that BCI-augmented therapy yields clinically meaningful motor improvements and also induces neurophysiological changes consistent with cortical reorganization [17].

4.3. Neurophysiological correlates of plasticity

Converging EEG and neuroimaging data provide mechanistic insights into BCI-induced plasticity. Multiple studies show that cortical reorganization will continuously change the brain following BCI training. Cantillo-Negrete et al. observed that BCI-trained patients indicate a more obvious ipsilesional cortical domain, and trends seem to have a greater corticospinal tract integrity than the control group, suggesting the motor pathway is enhanced. Ma et al. found that BCI therapy changed resting-state network topology. Improvements in FMA-UE correlated with changes in the visual and dorsal-attention networks on fMRI, which may imply re-adaptation of visuospatial/motor circuits. Overall, closed-loop BCI training promotes sensorimotor neuroplasticity in stroke patients in addition to improving behavior, according to accumulating EEG and imaging data [17-19].

5. Technical challenges and limitations

5.1. Signal stability and artifact suppression

Noninvasive EEG signals used in BCIs are unstable and prone to being influenced by noise. Many other signals may corrupt the interest motor signals, including muscle or eye artifacts, and external electromagnetic interference. Thus, a robust preprocessing, such as filtering, noise cancellation, is needed. However, real-time artifact removal remains a challenge. To elaborate, a prolonged use of BCI may cause slow shifts in SMR band power, for example, increased alpha with fatigue. Since EEG is decoding continuously, even a small non-neural change can deteriorate classifier performance [20]. Therefore, dynamic calibration and artifact-check algorithms are critical for maintaining reliable signal quality throughout the BCI session. Ensuring consistent signal accuracy in real-time continues to be an important ongoing challenge for BCI development.

5.2. Generalization across users

Performance varies widely between users. Even after training, some part of users (~10-30%) fail to achieve reliable control of MI-BCIs [21]. Stroke survivors may have even more variability due to lesion heterogeneity. This “BCI illiteracy” reflects inter-individual differences in neurophysiology and strategy [20]. Improved and customized machine-learning models and transfer-learning approaches are now being more advanced and able to reduce calibration time, but fully plug-and-play BCIs are not yet realized. In practice, each new user still requires extensive time for calibration and training, which limits the scalability of BCI therapy [22].

5.3. Training curve, cognitive load, and fatigue

An effective BCI session demands sustained concentration and motor imagery from patients. By imposing cognitive load on patients, this intensive session can induce mental fatigue, which may interfere with EEG measurement. Some studies show that fatigue symptoms will accumulate during training, although performance, which includes classification accuracy, may remain stable with

DOI: 10.54254/2753-8818/2025.LD25936

feedback and revision. Nonetheless, this often requires many sessions and takes weeks to learn to modulate their brain signal consistently. Rehabilitation protocols must strike a balance between session length and complexity to prevent overload. Especially for patients with post-stroke cognitive deficits or attentional impairment may struggle even more. Therefore, those paradigms need to be more adaptive or even gamified to sustain motivation [20].

5.4. Long-term adherence and wearable usability

Traditional BCI systems use multiple electrode EEG caps plus gel, which are not only time-consuming to set up but also uncomfortable for daily use. Ensuring consistent electrode contact over weeks or months is difficult, and patients may tire of the lengthy preparation. Wearable and dry-electrode EEG devices are emerging, but they often require frequent repositioning and are not as precise as the traditional ones. Moreover, maintaining motivation over long rehabilitation periods is significant; personalized feedback and intuitive interfaces are needed to improve adherence. At present, most stroke-BCI studies occur in the clinic. To facilitate at-home therapy, future work must prioritize miniaturized, automated hardware and streamlined calibration protocols that maintain signal quality without specialist assistance. Simplifying setup and ensuring patient comfort are essential for scaling BCI-enabled rehabilitation beyond the laboratory setting.

5.5. Ethical and privacy issues

Since neural data are mostly sensitive, BCIs raise important ethical considerations. In principle, the EEG signal may indicate cognitive states and intentions much beyond the rehabilitation tasks. Though patients often consent to brain monitoring, issues of data ownership and the extent to be used by third parties are still being debated. Some departments are beginning to solve those concerns, such as requiring independent notice and consent for each BCI session and any third-party data sharing [23]. In order to prevent the misuse of brain data, ethical practice often calls for strict privacy protections, open algorithms, and laws (such as HIPAA-equivalent measures for neurological data). Ensuring that patients retain control over their data and that it is used only with their informed consent is critical as BCI technology advances.

6. Conclusion

Different BCI paradigms aim to restore movement by linking neural signals to external devices. Motor-imagery BCIs decode a patient’s intention from EEG to trigger action; BCI-FES systems stimulate paralyzed muscles based on brain activity; BCI-driven robotics use exoskeletons or robotic arms to assist intended motions; closed-loop feedback provides real-time sensory reinforcement of the user’s own neural patterns. Each approach utilizes neuroplasticity through voluntary engagement and closing sensory-motor loops, helping patients gain more improvement in motor function compared to standard therapy. Nevertheless, there are many challenges still remain. EEG and other neural signals can be interfered with by artifacts. Therefore, it is important to develop stable signals with artifact suppression in real time. Individual variability also cannot be ignored; for instance, many patients cannot consistently modulate their brain signals, making it difficult to generalize decoding models across users. Furthermore, in real life, device wearability and user fatigue are often problems. Complex electrode caps and lengthy training can cause discomfort and thus reduced motivation, which further reduces adherence and effectiveness. BCIs also raise important ethical and privacy concerns since neural data are deeply personal.

DOI: 10.54254/2753-8818/2025.LD25936

In future, BCI stroke therapies will likely become more adaptive and integrated. Especially with recent AI development, multimodal systems combining EEG with additional sensors (e.g. EMG, fNIRS or motion trackers) and AI-driven decoders could enhance both signal accuracy and allow personalized training for each patient. Home-based platforms, including dry electrode headsets or portable exoskeletons, are promising to extend the therapy beyond the limitations of devices. Personalized protocols and real-time recalibration processes that adjust in real-time as a patient's neurological signals change are two examples of these developments. Besides, legal and ethical frameworks need to evolve with technology; precise rules for safeguarding patient privacy and neurological data must be established. To sum up, BCIs hold real potential to improve recovery outcomes after stroke. Realizing this potential will require incorporating and deploying lab innovations into practical therapies through both strict clinical trials and real-world attempts. Interdisciplinary cooperation will be key to success; patients, neuroscientists, engineers, and doctors must collaborate on patient-centred design and evaluation. Cutting-edge technology and careful, human-centred development can be combined to help the field lead BCI products to become successful rehabilitation solutions.

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