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REVIEW ARTICLE

BRAIN-COMPUTER INTERFACES USAGE IN NEUROREHABILITATION OF PATIENTS AFTER STROKE – SYSTEMATIC REVIEW

WYKORZYSTANIE INTERFEJSÓW MÓZG–KOMPUTER W NEUROREHABILITACJI PACJENTÓW PO UDARZE MÓZGU – PRZEGLĄD SYSTEMATYCZNY

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ABSTRACT

Introduction

Stroke is a leading cause of long-term disability worldwide, necessitating effective rehabilitation strategies. Currently, neurofeedback and brain-computer interfaces (BCI) based on electroencephalography (EEG) provide promising tools for controlled and precise neurorehabilitation.

Aim

To assess the therapeutic efficacy of EEG-based BCI usage in the neurorehabilitation process of post-stroke patients. The assessment focuses on the impact of motor functions and the induction of neuroplasticity.

Materials and methods

A systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. A comprehensive literature search across five major databases resulted in the final inclusion of 32 articles.

Results

Analysis revealed a diversity of BCI modalities, primarily utilizing motor imagery combined with virtual reality, functional electrical stimulation, and robotic exoskeletons to close the sensorimotor loop. Procedural parameters varied significantly: session durations ranged from brief tasks to one-hour protocols. The total number of sessions are also varied widely, from pilot studies to extended regimens of up to 80 sessions, averaging approximately 30 sessions. Regarding signal acquisition, most studies utilized high-density EEG setups (typically 20 or 32 leads). The cohorts predominantly included patients with chronic ischemic stroke, although healthy individuals were often recruited for system validation. Therapeutic effects

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were confirmed by significant improvements in clinical scales, particularly the Fugl-Meyer Assessment and neurophysiological markers, such as suppression of the mu rhythm.

Conclusions

Evidence supports that BCI-related methods significantly improve clinical outcomes in stroke survivors. However, the extent of positive neurological impact depends on the specific BCI modality and stroke characteristics. Future research requires standardized protocols to optimize dosage and include underrepresented patient groups.

Keywords: EEG, neurorehabilitation, neurofeedback, biofeedback, stroke

STRESZCZENIE

Wstęp

Udar mózgu stanowi jedną z głównych przyczyn długotrwałej niepełnosprawności na świecie, co podkreśla potrzebę opracowywania skutecznych strategii rehabilitacyjnych. Obecnie neurofeedback oraz interfejsy mózg–komputer (BCI) oparte na elektroencefalografii (EEG) stanowią obiecujące narzędzia umożliwiające precyzyjną i kontrolowaną neurorehabilitację.

Cel

Celem badania była ocena skuteczności terapeutycznej systemów BCI opartych na EEG w neurorehabilitacji pacjentów po udarze mózgu, ze szczególnym uwzględnieniem ich wpływu na funkcje motoryczne i indukcję neuroplastyczności.

Materiały i metody

Przegląd systematyczny przeprowadzono zgodnie z wytycznymi PRISMA (*Preferred Reporting Items for Systematic Reviews and Meta-Analyses*). Przeszukanie pięciu głównych baz danych pozwoliło na włączenie do analizy 32 artykułów.

Wyniki

Analiza wykazała szerokie spektrum modalności BCI, wykorzystujących głównie paradygmat wyobrażenia ruchowego w połączeniu z wirtualną rzeczywistością, funkcjonalną elektrostymulacją oraz egzoszkieletami robotycznymi, zamykającymi pętlę sensomotoryczną. Parametry proceduralne wykazywały znaczne zróżnicowanie: czas trwania pojedynczych sesji wahał się od kilkuminutowych zadań do pełnych, godzinnych protokołów. Liczba sesji była również znacznie zróżnicowana – od badań pilotażowych po intensywne cykle obejmujące 80 sesji. W zakresie monitorowania neurofizjologicznego dominowały systemy EEG wykorzystujące 20 lub 32 odprowadzenia. Kohorty badawcze składały się głównie z pacjentów po udarze niedokrwiennym w fazie przewlekłej oraz osób zdrowych służących do kalibracji systemów. Skuteczność terapeutyczną potwierdzały statystycznie istotne poprawy w skalach klinicznych, w szczególności w skali Fugl-Meyer Assessment, oraz zmiany w markerach neuroplastyczności, takich jak supresja rytmu μ.

Wnioski

Dowody potwierdzają, że metody oparte na BCI istotnie poprawiają wyniki kliniczne u osób po udarze. Zakres pozytywnego wpływu neurologicznego zależy od specyfiki zastosowanej metody BCI oraz charakterystyki udaru. Przyszłe badania powinny koncentrować się na standaryzacji protokołów w celu optymalizacji dawkowania terapii oraz uwzględnienia niedoreprezentowanych grup pacjentów.

Słowa kluczowe: EEG, neurofeedback, biofeedback, neurorehabilitacja, udar

Introduction

Cerebral strokes can lead to numerous neurological deficits, necessitating long-term rehabilitation in order to give patients a chance of at least partially regaining lost functions. In recent years, the incidence of strokes globally increased by 70%, same as number of deaths from stroke – by 44%, and disability-adjusted life-years lost – by 32% [1]. Despite advances in diagnostics, treatment methods, and public awareness of the importance of rapid response, stroke complications remain a key challenge currently faced by the healthcare system [2]. Neurofeedback (NF) is increasingly being used for patient rehabilitation, with promising results. This field has been developing in recent years, offering more treatment options [3]. However, it remains difficult to define the pattern and systematize research in this area. Our work compiles examples of the use of new brain-computer interface (BCI) methods in the rehabilitation of stroke patients published in recent years, as well as the results obtained with these methods.

Aim

The aim of this review was to determine whether the BCI-NF systems used in neurorehabilitation process show a positive impact on patient post-rehabilitation outcome. Additionally, the pattern in NF programming was sought to determine the most common solutions in this field among researchers. Ultimately, additional tools were screened, along with types of exercises and ways of evaluating the clinical progress.

Materials and methods

A literature review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [4]. The review focused on the use of BCI in the rehabilitation of stroke patients. The Embase, Scopus, PubMed, and Web of Science databases were searched. The article screening was performed using the following combination of keywords: "stroke" AND "EEG" AND "neurorehabilitation" AND ("biofeedback" OR "neurofeedback"). The results were filtered by language (English), publication date (2021–2025), and open access availability. The exclusion criteria were as follows: experimental studies (including animal studies and *in vitro* research); studies in children; studies on rehabilitation without the usage of electroencephalography (EEG); studies on patient without stroke; non-original articles (book chapters, abstracts, and posters); poor scientific quality (lack of methodology description, unrepresentative or too small sample size, insufficiently documented research results). The selection process is presented in Figure 1. Abstracts were revised, then full text articles were reviewed to retrieve the eligible articles. The revision was made independently by four researchers in October 2025. Duplicate records from the databases were removed. The following data were retrieved from reviewed publications: study

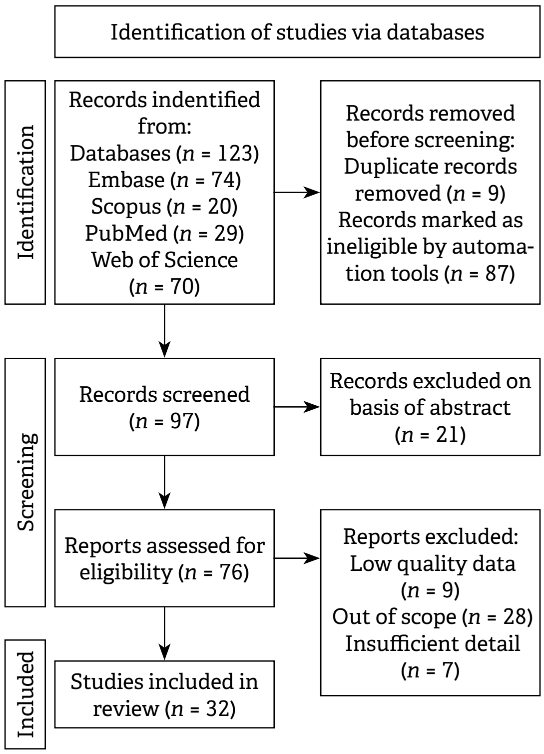


Figure 1. The article selection process in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines

methodology, therapeutic effect, number and length of rehabilitation sessions, number of EEG leads, analyzed brain area, activity patterns studied, and type of stroke. Analysis of data was conducted according to PRISMA recommendations.

Results

The systematic review process identified 32 studies meeting the inclusion criteria, which were subjected to detailed data extraction. The analyzed dataset encompasses a broad methodological spectrum, ranging from proof-of-concept studies involving healthy volunteers to advanced randomized controlled trials (RCTs) conducted on post-stroke populations.

After detailed analysis of stroke etiology within the cohorts, a significant research gap has been revealed (Table 1). The vast majority of studies specified the stroke type as ischemic or did not provide a specification, treating the stroke group as homogeneous. Only a few studies explicitly included this group in the analysis, usually in mixed models.

The BCI-NF term relates to a system which includes BCI and NF subsystems. BCI measures central nervous system activity and translates it into control signals for external devices [9]. NF measures a specific aspect of a person's brain activity in real time and then presents it back to them in an understandable form, for example, through visual or auditory feedback [5].

Table 1. Quantitative characteristics of the studies

Reference	Patients with a history of:		Healthy individuals	Total number of subjects
	Ischemic stroke	Hemorrhagic stroke		
Kim *et al.* 2025 [5]	25		–	25
Butet *et al.* 2025 [6]	15		–	15
Cha *et al.* 2025 [7]	15	–	–	15
Muller *et al.* 2025* [8]	–	–	30	30
Yuan *et al.* 2021 [9]	30	–	–	30
Kern *et al.* 2023 [10]	4	4	–	8
Afonso *et al.* 2024 [11]	8	2	–	10
Kim *et al.* 2024* [12]	–			
Lin *et al.* 2023 [13]	8		–	8
Phang *et al.* 2023 [14]	9		11	–
Remsik *et al.* 2022 [15]	3		–	3
Mak *et al.* 2022 [16]	226		–	226
Gangadharan *et al.* 2024 [17]	4		–	4
Li *et al.* 2022 [18]	16	8	–	24
Mayorova *et al.* 2023 [19]	18	–	–	18
Lakshminarayanan *et al.* 2024 [20]	–	–	12	12
Yue *et al.* 2023 [21]	16		–	16
Cantillo-Negrete *et al.* 2021 [22]	10	–	–	10
Carino-Escobar *et al.* 2023 [23]	–	–	18	18
Zhang X *et al.* 2025 [24]	7	3	20	30
Wang *et al.* 2021 [25]	–	–	5	5
Zhang W *et al.* 2025 [26]	–	–	8	8
Lee *et al.* 2021 [27]	11	–	11	22

**The researchers developed brain-computer interface-based neurofeedbacktechnology but did not implement it with patients in the published article*

Table 2. Rehabilitation and feedback characteristics

Reference	Type of rehabilitation	Task description	Feedback
Kim *et al.* 2025 [5]	MI-BCI training	The MI task of the wrist dorsiflexion	FES; visual: virtual avatar activation (only hands)
Butet *et al.* 2025 [6]	A bimodal EEG-fMRI based NF MI training	The kinesthetic MI	Visualization (EEG)
Cha *et al.* 2025 [7]	EEG-based MI-BCI training	Grasp session: grasp and release of the weak hand after appearance of the fixation cross; NF session: movement imagination leading to punching the target in the boxing game	Visual: a punch to the target in the boxing game
Muller *et al.* 2025 [8]	Multimodal EEG-fMRI NF MI training	MI task of the left-hand: raising and maintaining the visual representation of a ball moving along a one-dimensional vertical gauge	Visual: raise of the ball according to the brain activity level
Yuan *et al.* 2021 [9]	MI-BCI training with a pedaling robot intervention	Imagination of the lower limbs movement of the avatar and completing a pedaling task	Visual and auditory: virtual avatar activation; robotic: a pedaling training robot to drive lower limbs of the patient (pedaling game)
Kern *et al.* 2023 [10]	MI-BCI/BMI training with robotic hand intervention	The kinesthetic MI of opening the paralyzed hand	Robotic orthosis passively moving the hand
Afonso *et al.* 2024 [11]	Repetitive TMS followed by VR-BCI training	The MI of the left or right arm movement and virtual avatar rowing movement	Visual: virtual body from a first-person perspective; sensory: vibro–tactile (rowing game)
Kim *et al.* 2024 [12]	MI-BCI training	The MI task of the wrist dorsiflexion leading to movement of virtual arm to protect cheese pieces from mouse	FES; visual: virtual avatar activation
Lin *et al.* 2023 [13]	A VR-based MI training system with EMG-based real-time feedback	The MI task of reaching forward for the basketball, bending the arms, raising the arms, and throwing the basketball	Visual: virtual body from a first-person perspective (basketball game)
Phang *et al.* 2023 [14]	MP-BCI and MI-BCI training	Covert motor activities, including MP and MI; MP: preparing for lower limb motor movement; MI: kinesthetic MI of the lower limb	Visual: a computer screen, with varying shades of blue lines on a scalp image, visualizing the strength of the connections
Remsik *et al.* 2022 [15]	BCI-FES with multimodal feedback	Performing repeated hand grasping motions in either hand when cued – actual movement and imagery movement sessions – in order to move the cursor ball toward the target	Visual: movement of the cursor on the screen (ball-and-target game), the FES adjuvant, and the TDU stimulation
Mak *et al.* 2022 [16]	AR-based EEG-guided neglect detection (AREEN) system	The Starry Night Test paradigm: a user views randomly appearing and disappearing targets on the AR headset display	Visual: projecting the holographic visual cues dynamically in the visual space of the patient; tracking head position in real-time

Table 2. Cont.

Reference	Type of rehabilitation	Task description	Feedback
Gangadharan *et al.* 2024 [17]	MI-BCI training	The MI of the upper limb to control the vertical movement of the marble, so that it touches the target	Visual: movement of the marble according to the brain rhythms (the marble game)
Li *et al.* 2022 [18]	MI-BCI and MO-BCI training with multisensory feedback	The MI of "grabbing the object" or "putting the object down" with the video observation	Visual: points, cheering texts; robotic: exoskeleton hand robot passively moving the hand; auditory: commands, cheering texts
Mayorova *et al.* 2023 [19]	BCI-based task-focused training	Responding to the targeted letter: talking, moving a finger; focusing on the highlighted letter in order to type it	Visual: typing letters to create words
Lakshminarayanan *et al.* 2024 [20]	MI-BCI training with robotic control	The MI of the right/left hand movement in order to pop balloons positioned around the robot using its end effector	Visual and auditory: game – controlling a virtual iTbot robot; sensory stimulation: vibration
Yue *et al.* 2023 [21]	MO-BCI training with robotic hand intervention	Observation of biological or non-biological movement without any active movement of the patient	Visual: movement videos; robotic: exoskeleton hand robot passively moving the hand
Cantillo-Negrete *et al.* 2021 [22]	MI-BCI training with robotic hand intervention	The MI of the patient's paralyzed hand movement	Visual: faces with different degrees of smiling expressions; robotic orthosis passively moving the hand
Carino-Escobar *et al.* 2023 [23]	MI-BCI training with robotic hand intervention	The MI of the right hand: grasping and releasing the baseball placed under the palm of the right hand	Robotic orthosis passively moving the hand
Zhang X *et al.* 2025 [24]	MI-BCI training with robotic hand intervention	Voluntary movements: real executed grasping movements; passive movements: focusing on sensory feedback during passive move provided by the exoskeleton	Robotic orthosis passively moving the hand
Wang *et al.* 2021 [25]	MI-BCI training with robotic hand intervention	The MI of the right/left hand: "grasping task"; "hold" task without imagery	Visual: icons on the screen; robotic arm passively moving the hand
Zhang W *et al.* 2025 [26]	MI-BCI training with a teleoperation robotic system	The MI of the right/left hand in order to move the remote robotic arm eye movement fixation as a mode-switching method to control the robotic arm	Visual: remote robotic arm movement to place objects; sensory: vibration
Lee *et al.* 2021 [27]	MI and ME training	The ME: finger tapping; the MI: imagination of finger tapping	None (EEG data collection from finger tapping)

AR – augmented reality; BCI – brain-computer interface; BMI – brain-machine interface; EEG – electroencephalography; EMG – electromyography; FES – functional electrical stimulation; fMRI – functional magnetic resonance imaging; ME – motor execution; MI – motor imagery; MO – movement observation; MP – motor preparation; NF – neurofeedback; NMES – neuromuscular electrical stimulation; TDU – tactile display unit; TMS – transcranial magnetic stimulation; VR – virtual reality

A critical determinant of BCI system efficacy is the type of feedback provided to the user (Table 2). Based on the methodological analysis, the interventions were categorized into two main types, differentiated by the degree of sensorimotor loop engagement: visual and virtual feedback; somatosensory and proprioceptive feedback. Visual and virtual feedback is the most frequently (17 studies) employed modality, where the patient receives information about brain activity via a screen. These methods have evolved from simple two-dimensional bars and objects – such as controlling a ball on a vertical gauge or displaying specific graphics. Virtual reality (VR) setup allows for the observation of virtual limb movements from a first-person perspective, which enhances the sense of agency and ownership. In these paradigms, the feedback loop is closed exclusively through the visual channel. Somatosensory and proprioceptive feedback is considered more promising for inducing neuroplasticity [28], as it delivers sensory stimuli correlated with motor intention. Two subtypes were distinguished:

- robotic-assisted BCI (BCI-Robotic): these systems utilize hand exoskeletons or soft robotic gloves that physically execute finger movements upon the detection of motor imagery (MI) signals;
- BCI with functional electrical stimulation (FES) (BCI-FES/neuromuscular electrical stimulation): systems that trigger electrical stimulation of the muscles. One innovative approach combined tactile vibration stimulation with MI training to enhance the user's control efficiency.

The analysis of procedural parameters (session duration and frequency) revealed a lack of standardized protocols for BCI therapy dosage. The duration of a single session varied significantly, ranging from short, intensive task-oriented blocks lasting 8 minutes or 5-minute series [6,7], to full-scale rehabilitation sessions lasting 60 minutes [5]. In the case of extensive protocols combining patient preparation with active training, the total time extended up to 90 minutes (e.g., two 45-minute blocks) [8].

Six of the analyzed papers, particularly those testing novel control paradigms or innovative haptic solutions, relied on validation studies involving only healthy subjects. While these studies provide crucial data regarding the technical validity of BCI systems, direct translation of their results to clinical efficacy in patients with brain lesions requires cautious interpretation.

Similar discrepancies were noted in the total number of sessions. Most clinical trials (n = 11) oscillated between 2 and 4 weeks of therapy, offering from 10 to 20 therapeutic sessions. However, studies with fewer repetitions were also recorded (e.g., 10 or less sessions) [13,14,17,19], which complicates the direct comparison of the cumulative therapeutic effect between different methods.

Despite methodological diversity, the majority of the included RCTs demonstrated the superiority of BCI-based training over control groups (involving only classical rehabilitation process) regarding upper limb motor function improvement.

Considering the type of action performed by participants during trials, the great majority (n = 15) involved MI tasks. MI can be described as the mental representation of movement without any movement [29].

Among the analyzed studies, the most commonly used instrument for assessing clinical outcomes after MI-BCI rehabilitation was the Fugl-Meyer Assessment for Upper Extremities (FMA-UE), used in seven studies [6,10,11,15,18,22,30], whereas the Fugl-Meyer Assessment for Lower Extremities (FMA-LE) was used in one study [9].

Except for one study [5], researchers showed significant improvement in the Fugl-Meyer Assessment (FMA) [6,9–11,15,18,22,30].

However, even in the exceptional article, [5] proved positive effects in Medical Research Council scale score for muscle strength in the wrist extensor and active range of motion in wrist extension, despite the absence of significant change in FMA-UE compared to control group. The FMA-UE score was higher in a group without MI-NF.

Nevertheless, in this study the BCI-group received FES after successful MI, whereas in the control group FES was generated regardless of MI. Hereby, according to researchers, the clinical improvement in FMA-UE might be the consequence of a high number of FES or a placebo effect. Other clinical instruments, such as Action Research Arm Test (ARAT) [31,32], Wolf Motor Functional Test [33], and Modified Barthel Index [33], were used rarely and their outcome generally correlated with FMA. Christakou *et al.* [32] compared MI-BCI with robotic hand orthosis generating passive hand movement with conventional rehabilitation which included both passive and active motor tasks and found beneficial clinical effects of each method, with no significant distinction between them. Additionally, BCI was observed to improve the quality of life measured with the Stroke Impact Scale [5].

Only one study [14] involved motor preparation (MP) as an additional phase on MI-based rehabilitation and analyzed its influence on EEG signal and rehabilitation process. MP is an attentional phenomenon directed toward kinesthetic signals [14] and precedes MI or motor execution (ME).

Another task included in studies [13,21] is action observation (AO), during which the participant is shown a video clip presenting action performed by another person. AO is known to activate "mirror neurons" in the premotor and parietal cortex, resulting in increased cortical excitability of the primary motor cortex (M1) and is implicated in cognitive processes connected with movement planning and execution [34].

Although MI and AO rely on a similar action representation, there is a difference between them in aspects of the cognitive process. MI relies on mental representations stored in long-term memory to generate a motor image. Instead, during AO, visual information provided externally is held in working memory and does not depend on past experiences so much. Kim *et al.* [35] and Yue *et al.* [21] created BCI with robotic hand driven by mu supression during AO and proved significant improvement in the motor performance evaluated in ARAT and FMA-UE.

The strongest statistical evidence concerns improvements in the FMA-UE. In a study comparing NF with MI alone (without feedback), a significantly higher score increase was observed in the BCI group (p = 0.003), with the effect persisting at the one-month follow-up (p = 0.019) [5]. Similar results indicating significant improvement in FMA were reported in studies utilizing electrical stimulation [18].

Clinical outcomes are supported by evidence of brain neuroplasticity observed in EEG recordings. A key indicator of training efficiency was alpha rhythm suppression (8–13 Hz) in the sensorimotor cortex. It was demonstrated that BCI-NF training leads to significantly stronger mu suppression compared to a sham group in bilateral motor and parietal cortices [7]. Crucially, this effect was progressively strengthened in subsequent sessions, particularly in the ipsilesional M1 and supplementary motor area. This correlation suggests that BCI training effectively promotes the reorganization of cortical activation patterns necessary for motor initiation and functional recovery. The effects of the NF training are observed to be long-lasting, as it promotes structural changes and improves motor pathway function [6]. Adding NF to the rehabilitation training activates specific neural networks and enhances synaptic modification. This promotes neuroplasticity and learning through functional reorganization dependent on experience [8,24].

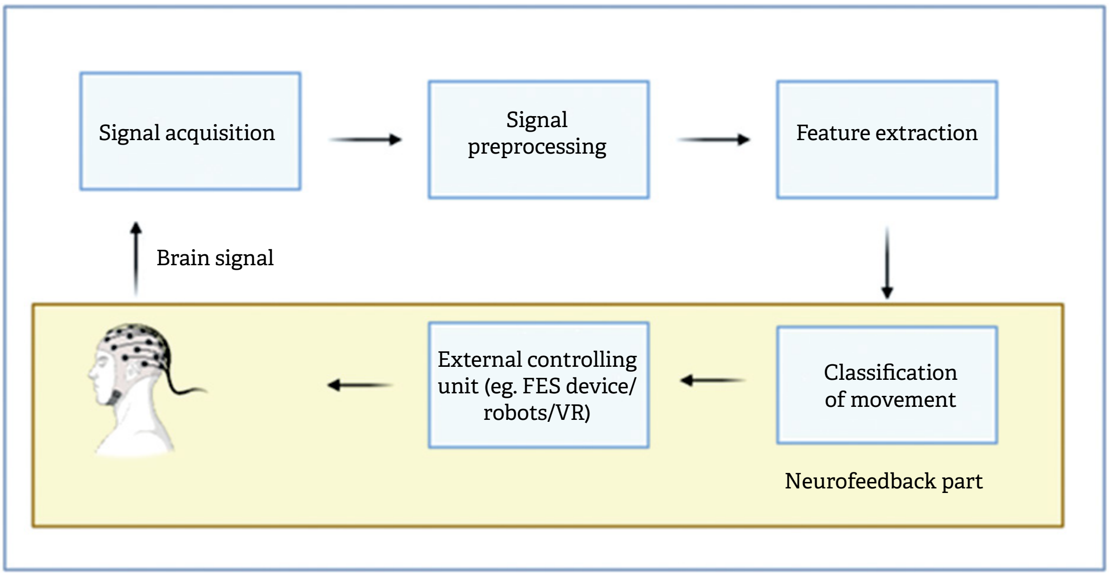
Rehabilitation with BCI-NF improves not only ipsilesional, but also contralesional hemisphere functional connectivity [5,7,11,17,18,23,25]. This highlights the supportive role of BCI-NF in motor recovery through enhanced complex bilateral brain activity and facilitated neuroplasticity [5,7,11,17,22,23]. Additionally, BCI-NF provides accurate and real-time feedback. Since it is often a single computing environment, small or negligible time delays appear. Appropriate time and space correlation play a significant role in clinical improvement [9,20].

Some technical aspects of BCI-NF systems were highlighted. Figure 2 presents the simplified structure of a generic BCI-NF system based on the framework proposed by Khan *et al.* [36].

First classification of BCI differentiates by the form of signal acquisition. It can be EEG-based when brain activity is being measured using the EEG [7,24,25]. Another type is based on functional magnetic resonance imaging, which uses magnetic resonance imaging to measure blood-oxygenation-level-dependent for real-time NF [37]. There are also systems combining two previous methods, called multimodal BCIs [8]. A second classification divides BCI systems according to the action required from the user when interacting with the system. MI systems involve the imagination of movement, which induces changes in mu and beta band activity, including event-related desynchronization (ERD) [5]. MP based BCIs use signals related to planning of limb movement [14]. P3-based BCIs utilize the P300 event-related potential which is triggered by stimulus of interest [19]. Attention index-based BCIs measure user's level of concentration using an index derived from EEG Fp1 channel [9].

Another division focuses on the external controlling unit. BCI-FES is met when the brain triggers FES to the muscles, resulting in actual movement of the limb [5]. BCI system is classified as BCI-Robotics when steering signal controls a mechanical device, such as robotic orthosis or exoskeleton, to assist or guide movement [24]. BCI-VR systems are met when their user controls an avatar or an object within a VR environment [36].

The specific type of control signal is a fundamental element for the design of any BCI system from both medical and technical standpoints. It influences patient's comfort during rehabilitation process, as well as signal acquisition and pre-processing methods. Each neuroparameter has different properties, such as frequency, values range, and missing values. That indicates the need to



FES – functional electrical stimulation, VR – virtual reality

Figure 2. The structure of a generic brain-computer interface neurofeedback system

choose proper signal interpolation and averaging methods to get the most accurate information possible out of collected time-series data. The choice of monitoring device brings questions related to latency and calibration errors handling methods.

Control signals deliver a quantitative measure for objectively assessing the patient's underlying brain activity. Analyzing these measures allows to draw conclusions about the impact of rehabilitation on the patient's neuroplasticity and functional recovery.

In reviewed studies, the following parameters were mentioned as selected measures: ERD – ten studies [5,7,8,10,11,13–15,22], asymmetry index – five studies [6,8,10,18,23] and beta/theta ratio – two studies [9,38].

ERD refers to a decrease in the power (or amplitude) of specific brain wave frequencies, primarily the mu (8–12 Hz) and beta (13–30 Hz) rhythms, that occur right before and during the execution or imagery of a movement [26]. This metric is described as a traditionally used method [7]. It is usually set with the opposite metric which is event-related synchronization (ERS) – it describes the increase of power of the same signals. For value analysis, ERD and ERS require time-frequency domain analysis and adjusting parameters such as frequency line and baseline period, which may affect the final result [38].

Asymmetry index, used interchangeably with laterality index (LI), is a measure assessing the inter-hemispheric balance between the two cerebral hemispheres [39]. It is calculated using the power of a specific brain oscillation band (like the mu or beta rhythm, 8-30Hz) measured during a task. LI formula is a ratio of ERD/ERS activities measured for cortical areas over both hemispheres.

Beta-theta ratio represents a ratio of theta to beta brain waves power [14]. It's being measured with EEG device. Further signal analysis to calculate the ratio is performed using well-established algorithms, such as Fast Fourier Transform and spectral analysis methods [14].

Considering the patient's comfort and signal pre-processing steps, beta-theta ratio might be a choice for a control signal in BCI system, although further assessment is needed to confirm this statement [38].

Khan *et al*. [36] indicates that BCI-VR systems could be the most optimized choice for stroke patients' rehabilitation. However, BCI-Robotics system could be a more efficient choice for patients with no or little motor function. Moreover, BCI systems can be more personalized than traditional rehabilitation. Since these methods can be specifically adapted, they help even with patients with severe motor impairment, as long as instructions of the task are clear [15]. Additionally, according to studies, patients find BCI systems easy to use [22]. Moreover, despite the neurophysiological mechanism of MI being still unclear [40,41], its effectiveness has been proved in motor recovery after stroke, especially as the additional method to conventional motor therapy [30,31,42] and may be successfully used even in elderly patients [32,33]. An additional advantage of MI is the possibility of its use even in the early phase of stroke recovery, when active movements are unattainable due to paresis.

Furthermore, rehabilitation programs using BCI and NF were described as more fascinating, absorbing, and engaging [6,13,18,20], thereby leading to increased level of concentration [9,12,17,20]. This was achieved by asking to maintain specific brain activity based on provided visualization and operant conditioning with reward system [12,13,17,20]. A wide range of multimodal feedback types, such as visual, auditory, and somatosensory feedback, contribute to making rehabilitation more attractive and help patients to focus on the task. Gamification and basing on the reward system boost confidence of the patients and let them deeply immerse into the game. As a result, they can perceive it more as an entertainment rather than rehabilitation, leading to decreased stress level during the recovery process.

Although there are many strengths of BCI-NF method, some disadvantages exist. Occasionally, tiredness and fatigue occur, since the rehabilitation task can be challenging and cognitively demanding for the patient [12,16]. To minimize the risk of exhaustion, training sessions should have an optimized duration and assigned exercise should not be too complex. In some cases the BCI illiteracy can occur [23]. It is defined as difficulty or inability to control BCI [43,44]. Patients with such a problem require determination of a more suitable type of BCI for better performance.

Conclusions

BCI-NF represents a promising and rapidly developing method supporting motor recovery after stroke. The reviewed studies consistently demonstrate that this solution can effectively enhance neuroplasticity by modulating cortical activity. Across trials, MI remains the most used task paradigm; however, even more promising results are observed with AO combined with MI, potentially the most expandable way for neurostimulation in patients. Nevertheless, despite these advantages, numerous limitations persist. Certain patients encounter fatigue or a lack of proficiency in brain-computer interface technology, necessitating the selection of customized systems and the optimization of training protocols. Technical obstacles – including cumbersome equipment, calibration difficulties, and elevated costs – continue to hinder the extensive clinical deployment of these technologies. From the perspective of the researcher and the patient, the most comfortable and effective way to evaluate NF is the beta/theta ratio, which is still used in very few studies. Methodologically, numerous studies depend on small sample sizes, predominantly feature survivors of ischemic strokes, or are executed on healthy individuals, thereby constraining the generalizability of the results obtained. To comprehensively establish the clinical efficacy of BCI-NF, forthcoming research should concentrate on larger, methodologically rigorous trials that encompass diverse stroke populations, standardized outcome measures, and direct comparisons among various BCI paradigms. Additionally, further investigation into the identification of optimal control signals and task protocols will be crucial for the refinement and personalization of BCI-NF-based therapeutic interventions.

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