Review

Brain-Computer Interface Robotics for Hand Rehabilitation

After Stroke: A Systematic Review

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Abstract

Background: Electroencephalography-based brain-computer interfaces (BCI) that allow the control of robotic devices to support stroke patients during upper limb rehabilitation are increasingly popular. Hand rehabilitation is focused on improving dexterity and fine motor control and is a core approach for helping stroke survivors regain activities of daily living. This systematic review examines recent developments in BCI-robotic systems for hand rehabilitation and identifies evidence-based clinical studies on stroke patients.

Methods: A search for January 2010-October 2019 articles using Ovid MEDLINE, Embase, PEDro, PsycINFO, IEEE Xplore and Cochrane Library databases was performed. The selection criteria included BCI-hand robotic systems for rehabilitation in various development stages involving tests on healthy human subjects or stroke survivors. Data fields include those related to study design, participant characteristics, technical specifications of the system, and clinical outcome measures.

Results: 30 studies were identified as eligible for qualitative review and among these, 11 studies involved testing a BCI-hand robot on chronic and subacute stroke patients. Statistically significant improvements in motor assessment scores relative to controls were observed for two BCI-hand robot interventions. The degree of robot control for the majority of studies was limited to triggering the device to perform grasping or pinching movements using motor imagery. Most employed a combination of kinaesthetic and visual response via the robotic device and display screen, respectively, to match feedback to motor imagery.

Conclusion: Most studies on BCI-robotic systems for hand rehabilitation report systems at prototype or pre-clinical stages of development. Some studies report statistically significant improvements in functional recovery after stroke, but there is a need to develop a standard protocol for assessing technical and clinical outcomes so that the necessary evidence base on efficiency and efficacy can be developed.
Keywords: brain-computer interface, electroencephalography, motor imagery, action observation, robot-assisted rehabilitation, hand, wrist, stroke, therapy

**Background**

There is growing interest in the use of robotics within the field of rehabilitation. This interest is driven by the increasing number of people requiring rehabilitation following problems such as stroke (with an ageing population), and the global phenomenon of insufficient numbers of therapists able to deliver rehabilitation exercises to patients [1,2]. Robotic systems allow a therapist to prescribe exercises that can then be guided by the robot rather than the therapist. An important principle within the use of such systems is that the robots assist the patient to actively undertake a prescribed movement rather than the patient’s limb being moved passively. This means that it is necessary for the system to sense when the patient is trying to generate the required movement (given that, by definition, the patient normally struggles with the action). One potential solution to this issue is to use force sensors that can detect when the patient is starting to generate the movement (at which point the robot’s motors can provide assistive forces). It is also possible to use measures of muscle activation (EMGs) to detect the intent to move [3]. There is, however, growing interest in the potential of using measures of brain activity to identify when a patient is trying to generate a movement—referred to as Brain Computer Interfaces, or BCIs. This interest in BCIs is motivated by idea that the rehabilitation process can be enhanced by particular types of brain activity related to imagining the movement [4]. There is a long history of using robotic devices for stroke rehabilitation [5,6] and in the last decade, there has been a concerted effort by groups of clinicians, neuroscientists and engineers to integrate these systems with incoming brain signals to enhance the efficacy and effectiveness of stroke rehabilitation. The purpose of this
manuscript is to review the current state-of-the-art of existing brain-computer ‘closed loop’
interfaces in terms of the technological readiness of existing systems, and the evidence for
their clinical effectiveness.

BCIs allow brain state-dependent control of robotic devices to aid stroke patients during
upper limb therapy and have been gaining research attention since their first implementation
more than a decade ago [7,8]. Graimann et al. [4] defined a BCI as an artificial system that
provides direct communication between the brain and a device based on the user’s intent;
bypassing the normal efferent pathways of the body’s peripheral nervous system. A BCI
recognises user intent by measuring brain activity and translating it into executable
commands usually performed by a computer, hence the term “brain-computer interface”.

Most robotic devices used in upper limb rehabilitation exist in the form of exoskeletons or
end-effectors. Robotic exoskeletons (i.e., powered orthoses, braces) are wearable devices
where the actuators are biomechanically aligned with the wearer’s joints and linkages;
allowing the additional torque to provide assistance, augmentation and even resistance during
training [9]. In comparison, end-effector systems generate movement through applying forces
to the most distal segment of the extremity via handles and attachments [9]. Rehabilitation
robots are classified as Class II-B medical devices (i.e., a therapeutic device that administers
the exchange of energy, mechanically, to a patient) and safety considerations are important
during development [10,11]. Most commercial robots are focused on arms and legs, each
offering a unique therapy methodology. There is also a category of device that target the hand
and finger. Hand and finger rehabilitation are core component in regaining activities of daily
living (ADL) as many ADLs require dexterous and fine motor movements (e.g. grasping and
pinching). Thus, the current review is focused on devices that have been designed specifically for wrist, hand and finger rehabilitation.

The potential of BCIs has gained considerable attraction because the neural activity involved in the control of the robotic device may be a key component in the rehabilitation itself. For example, mental rehearsal of movement is thought to activate some of the neural networks involved in movement execution (ME) [12–15]. The resulting rationale is that encouraging the use of motor imagery (MI) (i.e., the imagination of movement without execution) could increase the capacity of the motor cortex to control major muscle movements and decrease the necessity to use neural circuits damaged post-stroke. The scientific justification for this approach was first provided by Jeannerod [15] who suggested that the neural substrates of MI are part of a shared network that is also activated during the simulation of action by the observation of action (AO) [15]. These ‘mirror neuron’ systems are thought to be an important component of motor control and learning [15] - hence the belief that stimulating these systems could aid rehabilitation.

A recent meta-analysis of the neural correlates of action (MI, AO and ME) quantified ‘conjunct’ and ‘contrast’ networks in the cortical and subcortical regions [12]. This analysis, which took advantage of open-source historical data from fMRI studies, reported consistent activation in the premotor, parietal and somatosensory areas for MI, AO and ME. Predicated on such data, researchers have reasoned that stimulating MI should cause activation of the neural substrates that are also involved in controlling movement and there have been a number of research projects that have used AO in combination with MI in neurorehabilitation [16–18] and motor learning studies [19,20] over the last decade.
The strategy of BCI-robot systems in rehabilitation is to recognise the patient's intention to move or perform a task via an electroencephalography acquisition system [21], and then use the robotic device to provide assistive forces in a manner that mimics the actions of a therapist during standard therapy sessions [22]. The resulting feedback is patient-driven and is designed to aid in closing the neural loop from intention to execution. This process is said to promote use-dependent neuroplasticity within intact brain regions and relies on the repeated experience of initiating and achieving a specified target [23,24]; making the active participation of the patient in performing the therapy exercises an integral part of the motor re-learning process [25,26]. It is important to note that whilst the rationale underpinning the conjecture that BCI-robot systems could be useful in hand rehabilitation is reasonable, it is just a conjecture that requires empirical support.

Electroencephalography (EEG) is currently the instrument of choice for data acquisition in BCI systems because it is non-invasive, easy to use and can detect relevant brain activity with high temporal resolution [27,28]. In principle, the recognition of MI activity via EEG can allow the control of a device independent of muscle activity [4]. It has been shown that MI-based BCI can discriminate motor intent by detecting event-related spectral perturbations (ERSP) [21,29] and/or event-related desynchronisation/synchronisation (ERD/ERS) patterns in the μ (9-11 Hz) and β (14-30 Hz) sensorimotor rhythm of EEG signals [29]. However, EEG also brings with it some challenges—these neural markers are often concealed by various artefacts and may be difficult to recognise through the raw EEG signal alone. Thus, signal processing (via feature extraction and classification) is a vital part of obtaining a good MI signal for robotic control.
One implication of using MI and AO to justify the use of BCI approaches is that great care must be taken with regard to the quality of the environment in which the rehabilitation takes place. An important feature of MI is that, by definition, the patient must be able to imagine the movement. Likewise, AO requires the patients to clearly see the action. This suggests that the richness and vividness of the visual cues provided is an essential part of an effective BCI system. It is also reasonable to assume that feedback is important within these processes and thus the quality of feedback should be considered as essential. Finally, motivation is known to play an important role in promoting active participation during therapy [26,30]. Thus, a good BCI system should incorporate an approach (such as gaming and positive reward) that increases motivation. Recent advances in technology make it far easier to create a rehabilitation environment that provides rich vivid cues, gives salient feedback and is motivating. For example, the rise of immersive technologies, including virtual reality (VR) and augmented reality (AR) platforms [31,30,32], allows for the creation of engaging visual experiences that have the potential to improve a patient’s self-efficacy [33] and thereby encourage the patient to maintain the rehabilitation regime. One specific example of this is visually amplifying the movement made by a patient when the movement is of limited extent so that the patient can see their efforts are producing results [34].

In this article, we review the development of BCI-robotic systems for hand rehabilitation and capture clinical studies involving stroke patients. Our goal was to address three critical questions for understanding the current value and potential of BCI-based robotic therapy:

(1) Identify how BCI technologies are being utilised in controlling robotic devices for hand rehabilitation. Our focus was on the study design and the tasks that are employed in setting up a BCI-hand robot therapy protocol.
Document the state-of-art of BCI systems. Because BCI for rehabilitation is still an emerging field of research, we expected that most studies would be in their proof-of-concept or clinical testing stages of development. Our purpose was to determine the limits of this technology in terms of: (a) resolution of hand MI detection and (b) the degree of which we can have robotic control.

(3) Evaluate the clinical significance of BCI-hand robot systems by looking at the outcome measures in motor recovery and determine if a standard protocol exists for these interventions.

It is important to note that there have been several recent reviews exploring BCI for stroke rehabilitation. For example, Monge-Pereira et al. [35] compiled EEG-based BCI studies for upper limb stroke rehabilitation. Their systematic review (involving 13 clinical studies on stroke and hemiplegic patients) reported on research methodological quality and improvements in the motor abilities of stroke patients. Cervera et al. [36] performed a meta-analysis on the clinical effectiveness of BCI-based stroke therapy among 9 randomised clinical trials (RCT). McConnell et al. [37] reviewed and provided insights from a total of 110 robotic devices with brain-machine interfaces for hand rehabilitation post-stroke. These reviews, in general, have reported that such systems provide improvements in both functional and clinical outcomes in pilot studies or trials involving small sample sizes. Thus, the literature indicates that EEG-based BCI are a promising general approach for rehabilitation post-stroke.

The current work complements these previous reports by focusing on a systematic review of the rehabilitation of the fine motor skills associated with hand movement, and profiling BCI-robot systems for the hands with their corresponding technical and clinical implementations.
Methods

Protocol Registration
Details of the protocol for this systematic review were registered on the International Prospective Register of Systematic Reviews (PROSPERO) and can be accessed at www.crd.york.ac.uk/PROSPERO (ID: CRD42018112107).

Search Strategy and Eligibility
An in-depth search of articles from January 2010 to October 2019 was performed on Ovid MEDLINE, Embase, PEDro, PsycINFO, IEEE Xplore and Cochrane Library. Only full-text articles published in English were selected for this review. Table 1 shows the combination of keywords used in the literature searching.

Table 1. Keyword Combinations

| Set 1 (OR) | Set 2 (OR) | Set 3 (OR) |
|------------|------------|------------|
| Brain-computer interface/BCI | Stroke (rehabilitation/therapy/treatment/recovery) | Robotic (exoskeleton/orthosis) |
| Electroencephalography/EEG | Motor (rehabilitation, therapy/treatment/recovery) | Powered (exoskeleton/orthosis) |
| Brain-machine interface/BMI | Neurorehabilitation | Robot |
| Neural control interface AND Mind-machine interface | Neurotherapy | Device |
| AND | Hand (rehabilitation/therapy/recovery/exercises/movement) | |

The inclusion criteria for the articles were: (1) publications that reported the development of an EEG-based BCI; (2) studies targeted towards the rehabilitation of the hand after stroke; (3) studies that involved the use of BCI and a robotic device (e.g., exoskeleton, end-effector type, platform-types, etc.); (4) studies that performed a pilot test on healthy human subjects or a clinical trial with stroke patients. The articles were also screened for the following exclusion
criteria: (1) studies that targeted neurological diseases other than stroke; (2) studies that used other intention sensing mechanisms (electromyography/EMG, electrooculography/EOG, non-paretic hand, other body parts, etc.).

Two authors performed independent screenings of titles and abstracts based on the inclusion and exclusion criteria. The use of a third reviewer was planned a priori in cases where a lack of consensus existed around eligibility. However, consensus was achieved from the first two authors during this stage. Full-text articles were then obtained, and a second screening was performed until a final list of studies was agreed to be included for data extraction.

Data Extraction

The general characteristics of the study and their corresponding results were extracted from the full-text articles by the reviewers following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) checklist. Data fields included those related to study design, participant characteristics, technical specifications of the system, and technical and experimental results. For studies involving stroke patients, clinical outcomes were obtained based on muscle improvement measures such as Fugl-Meyer Motor Assessment (FMMA) scores [38], Action Research Arm Test (ARAT) scores [39], United Kingdom Medical Research Council (UK-MRC) muscle grade [40], Grip Strength (GS) Test and Pinch Strength (PS) Test scores (i.e., kilogram force collected using an electronic hand dynamometer) among others.
Quality Assessment

Technological Readiness

We first assessed the development stages of the systems used in the studies extracted. By performing a Technological Readiness Assessment (TRA), we were able to determine the maturity of the systems via a Technology Readiness Level (TRL) scale of 1-9 and quantify its implementation in a research or clinical setting. Since a BCI-robot for rehabilitation can be categorised as a Class II-B medical device we have adapted a customised TRL scale to account for these requirements [41].

Clinical Use

A methodological quality assessment was also performed for clinical studies based on the Physiotherapy Evidence Database (PEDro) Scale [42]. This scale evaluates studies with a checklist of 11 items based on experts’ consensus criteria in physiotherapy practice. The complete details of the criteria can be found online [43]. A higher score in the PEDro scale (6 and above) implied better methodological quality but are not used as a measure of validity in terms of clinical outcomes. Pre-defined scores from this scale were already present in studies appearing in the PEDro search. However, studies without PEDro scores or are not present in the PEDro database at all had to be manually evaluated by the authors against the 11-item checklist (five of seven studies).
Results

Search Results
Figure 1 shows the study selection process and the number of articles obtained at each stage.

A total of 590 studies were initially identified. After deduplication, 330 studies underwent title and abstract screening. Forty six studies passed this stage and among these, 16 were removed after full-text screening due to the following reasons: insufficient EEG and robotic data [44–50], the study was out of scope [51–53], the study design was not for hand/finger movement [54–57], no robot or mechatronic device was involved in the study [58,59]. A final list with 30 studies was identified as eligible for qualitative review. Among the 30 studies, 11 [60–70] were involved in testing the BCI-hand robot system on chronic and subacute stroke.

Figure 1. Study Selection Flowchart
patients ([60,65] are RCTs) while the rest involved testing on healthy participants [71–89].

Table 2 shows a summary of the relevant data fields extracted from these studies.

[Table 2 Around Here]

Technology Evaluation

EEG Acquisition

The choice of EEG system as well as the type of electrodes provides a technical trade-off and affects the session both in terms of subjective experiences (i.e., ease-of-use, preparation time, cleaning, comfortability) and data performance. Due to the presence of a conducting gel/solution, standard “wet” electrodes provide a degree of confidence in preventing signal disruption within a short duration usually enough for a standard stroke therapy session. However, this also makes the setup, use and cleaning in the experiment more challenging, non-ambulatory and reliant on a specialised laboratory setup [4]. Conversely, dry electrodes offer an accessible, user-friendly and portable alternative by using dry metal pins or coatings that comb through hair and come in contact directly with the scalp. The signal fidelity of dry electrodes is still a matter of debate in the BCI community. A systematic comparison between dry passively-amplified and wet actively-amplified electrodes reported similar performance in the detection of event-related potentials (ERP) [90]. However, for a study involving dry active electrodes [91], high inter-electrode impedance resulted in increased single-trial and average noise levels as compared to both active and passive wet electrodes. In classifying MI, movement-related artefacts adversely affect active dry electrodes, but these can be addressed through a hybrid system of other physiological sensors to separate sources [92].
The EEG acquisition systems involved in the studies ranged from low-cost devices having few electrode channels (2-15 gel or saline-soaked silver/silver chloride [Ag/AgCl] electrodes) to standard EEG caps that had higher spatial resolution (16-256 gel or saline-soaked Ag/AgCl electrodes). The placement of EEG channels was accounted for by studies involving MI (N=21). This allowed us to determine the usage frequency among electrodes and is presented in Figure 2 as a heat map generated in R Studio (using the packages: “akima”, “ggplot2” and “reshape2”) against the 10-20 international electrode placement system.

Figure 2. EEG Channel Usage across Motor Imagery Studies (N=21)
It can be seen that the EEG channels used for MI studies are concentrated towards electrodes along the central sulcus (C) region and the frontal lobe (F) region of the placement system where the motor cortex strip lies. Among these, C3 (N=17) and F3 (N=14) were mostly used, presumably because a majority of the participants were right-handed. The next most frequent were C4 (N=13) and the electrodes F4, Cz and CP3 (N=10).

Signal Processing: Feature Extraction and Classification

It is necessary to process EEG data if they are to be used as a control signal. First, the data need to undergo a series of pre-processing routines (e.g., filtering and artefact removal) before feature extraction and classification for use as a control signal for the robotic hand. Feature extraction involves recognising useful information (e.g., spectral power, time epochs, spatial filtering) for better discriminability among mental states. For example, the common spatial patterns (CSP) algorithm is a type of spatial filter that learns and maximises the variance of band pass-filtered EEG from one class to discriminate it to the other [93].

In the EEG-based BCI studies examined, it was found that the feature extraction and classification techniques were variable between systems. Table 3 provides a summary of pre-processing, feature extraction and classification techniques across the studies. There was a wide variation in the implemented signal processing strategies, but a unifying theme across studies was the attempt to: (i) discriminate mental states recorded in EEG across different manual tasks; (ii) classify the different states to produce a viable signal.

| Study          | Pre-Processing | Feature Extraction | Classification | Hand Task   |
|----------------|----------------|--------------------|----------------|-------------|
| Ang et al. [60] | Band-pass (0.05-40 Hz) | Filter Bank Common Spatial Pattern | Calibration model (unspecified) | MI vs rest |
| Study              | Filter Parameters                        | EEG Analysis | Classification Method                                      | Task                                                                 |
|--------------------|------------------------------------------|--------------|-----------------------------------------------------------|----------------------------------------------------------------------|
| Barsotti et al. [61] | Band-pass (8-24 Hz)                       | ERD (β and μ-decrease), CSP | SVM with linear kernel                                    | MI vs rest                                                           |
| Bauer et al. [82]   | Band-pass (6-16 Hz using zero-phase lag FIR) | ERD (β-decrease) | Linear autoregressive model based on Burg Algorithm        | MI vs rest                                                           |
| Bundy et al. [62]   | Unspecified                               | ERD (β and μ-decrease) | Linear autoregressive model                               | MI (affected, unaffected) vs rest                                    |
| Chowdhury et al. [63]| Band-pass (0.1 Hz-100 Hz), Notch (50 Hz)  | CSP Covariance-based, ERD/ERS (β and μ-change) | SVM with linear kernel, Covariate Shift Detection (CSD)-based Adaptive Classifier | left vs right MI                                                  |
| Coffey et al. [77]  | Band-pass (0.5 Hz-30 Hz), Notch (50 Hz)   | CSP Covariance-based | Linear Discriminant Analysis (LDA) classifier             | MI vs rest                                                           |
| Diab et al. [88]    | Unspecified                               | Time epochs (unspecified) | Artificial Neural Network (ANN)-based Feed Forward Back Propagation | Non-MI open vs closed                                                   |
| Frolov et al. [65]  | Band-pass (5-30 Hz), FIR (order 101), IIR notch Chebyshev type I filter (50 Hz) | Time epochs (10 s) | Bayesian-based EEG covariance classifier [95] | MI (affected, unaffected) vs rest                                    |
| Ono et al. [66]     | Band-pass (0.5-30 Hz), notch (50 or 60 Hz) | Time epochs (700 ms), ERD (μ-decrease) | Linear Discriminant Analysis (LDA) classifier             | MI vs rest                                                           |
| Ramos-Murguialday et al. [80] | Unspecified | Time epochs (5 s), Spatial filter, ERD/ERS (β and μ-change) | Linear autoregressive model                               | MI vs rest                                                           |
| Vukelic and Gharabaghi [84] | High-pass (unspecified)                   | ERD (β-decrease) | Linear autoregressive model based on Burg Algorithm        | MI vs rest                                                           |
| Witkowski et al. [86] | Band-pass (0.4-70 Hz), Laplacian filter | ERD/ERS (β and μ-change) | Linear autoregressive model based on Yule-Walker algorithm | MI vs rest                                                           |

SVM = Support Vector Machines, FIR = Finite Impulse Response, IIR = Infinite Impulse Response


Robot-Assisted Rehabilitation

Robotic hand rehabilitation systems provide kinaesthetic feedback to the user during BCI trials. Most of these devices are powered by either DC motors, servomotors or pneumatic actuators that transmit energy via rigid links or Bowden cables in a tendon-like fashion. The studies in this review included single-finger [69–71], multi-finger [67] (including EMOHEX [63,64,72]), full hand gloves [73,74] (including mano: Hand Exoskeleton [75] and Gloreha [76]) and full arm exoskeletons with isolated finger actuation (BRAVO-Hand [61]). Nine of the studies [62,72,73,75,77–81] presented their novel design of a hand rehabilitation device within the article while some reported on devices reported elsewhere (i.e., in a previous study of the group or a research collaborator). Two commercially-available devices were also used: AMADEO (Tyromotion, Austria) is an end-effector device used in 3 studies [82–84], and Gloreha (Idrogenet, Italy) is a full robotic hand glove used by Tacchino et al. [76]. AMADEO and Gloreha are both rehabilitation devices that have passed regulatory standards in their respective regions. AMADEO remains the gold standard for hand rehabilitation devices as it has passed safety and risk assessments and provided favourable rehabilitation outcomes. The International Classification of Functioning, Disability and Health (ICF) provides three specific domains that can be used to assess an intervention of this kind: improving impairments, supporting performance of activities and promoting participation [96,97]. In this case, a gold standard device not only prioritises user safety (established early in the development process) but also delivers favourable outcomes in scales against these domains. Figure 3 shows the main types of robotic hand rehabilitation devices.
Figure 3. Robotic hand rehabilitation devices: a) An end-effector device (Haptic Knob) used in one of the extracted studies [60,98], b) a wearable hand exoskeleton/orthosis.

Quality Assessment

A Technology Readiness Assessment (TRA) was performed for each study and the Technology Readiness Levels (TRL) are presented in Table 4. While some of the system components (especially among robotic devices) were commercially available (having TRL 9+), we performed a TRA on the whole system (the interaction between BCI and robotics) to provide an evaluation of its maturity and state-of-the-art development with regard to rehabilitation medicine. We further assessed the TRL of each system at the time of the publication and its subsequent development.

Table 4. Technology Readiness Assessment of the BCI-Hand Robot Systems

| Levels | Description                                      | Studies                                                                 |
|--------|--------------------------------------------------|-------------------------------------------------------------------------|
| TRL 1  | Lowest level of technological readiness          |                                                                          |
|        | Literature reviews and initial market surveys    |                                                                          |
|        | Scientific application to defined problems       |                                                                          |
| TRL 2  | Generation of hypotheses                         |                                                                          |
|        | Development of research plans and/or protocols   |                                                                          |
TRL 3

- Testing of hypotheses – basic research, data collection and analysis
- Testing of design/prototype – verification and critical component specifications
- Initial proof-of-concept in limited amount of laboratory/animal models

Most studies from the prototype group (N=18) [71–87,89]

TRL 4

- Proof-of-concept of device/system in defined laboratory/animal models
- Safety testing – problems, adverse events and potential side effects

Witkowski et al., 2014 [88]

TRL 5

- Comparison of device/system to other existing modalities or equivalent devices/systems
- Further development – testing through simulation (tissue or organ models), animal testing
- Drafting of Product Development Plan

Barsotti et al., 2015 [61], Ono et al., 2016 [66], Chowdhury et al., 2018-b [63], Tsuchimoto et al., 2019 [69]

TRL 6

- Small scale clinical trials (Phase 1) – under carefully controlled and intensely monitored clinical conditions

Carino-Escobar et al., 2019 [70], Chowdhury et al., 2018-c [64], Norman et al., 2018 [67], Wang et al., 2018 [68]

TRL 7

- Clinical trials (Phase 2) – safety and effectiveness integration in operational environment

Ang et al., 2014 [60], Frolov et al., 2017 [65]

TRL 8

- Clinical trials (Phase 3) – evaluation of overall risk-benefit of device/system use
- Confirmation of QSR compliance
- Awarding of PMA for device/system by CDRH or equivalent agency

TRL 9

- The device/system may be distributed/marketed

QSR = Quality System Requirements, PMA = Premarket Approval, CDRH = Center for Devices and Radiological Health
Clinical Evaluation

Studies with Stroke Patients (Clinical Group)

A total of 208 stroke patients (with sample size varying 3-74) were involved in the 11 clinical studies. One study [60] reported a 3-armed RCT with control groups as device-only and SAT while another study [65] was a multi-centre RCT with sham as the control group. Five studies were uncontrolled – where the aims were either to study classification accuracies during sessions [61], to monitor clinical outcomes improvement from Day 0 until the end of the programme [62,70] or both [64,67]. Two studies [68,69] compared effects of the intervention against SHAM feedback. Another study [63] compared the classification accuracies of healthy and hemiplegic stroke patients against two BCI classifiers while the remaining study [66] compared classification accuracies from stroke patients who receive congruent or incongruent visual and kinaesthetic feedback.

Most of the studies adopted FMMA, ARAT and GS measurements to assess clinical outcomes. Six studies [60,62,64,65,68,70] reported patient improvement in these measures when subjected to BCI-hand robot interventions; in contrast with their respective controls or as recorded through time in the programme. For Ang et al. [60], FMMA Distal scores were reported in weeks 3, 6, 12 and 24 and the BCI-device group (N=6) yielded the highest improvement in scores across all time points as compared to the device only (N=8) and SAT (N=7) groups. Bundy et al. [62] reported an average of 6.20±3.81 improvement in the ARAT scores of its participants (N=10) in the span of 12 weeks while Chowdhury et al. [64] reported a group mean difference of +6.38 kg (p=0.06) and +5.66 (p<0.05) in GS and ARAT scores, respectively (N=4). Frolov et al.’s [65] multi-centre RCT reported a higher improvement in the FMMA Distal, ARAT Grasp and ARAT Pinch scores of the BCI-device group (N=55) when compared to the control/SHAM group (N=19), but not in the ARAT Grip
scores where the values are both equal to 1.0 with p<0.01 for the BCI-device group and p=0.045 for the control.

Studies with Healthy Participants (Prototype Group)

The studies which involved pilot testing on healthy human participants had a combined total of individuals (sample size ranging from 1-32) who had no history of stroke or other neurological diseases. Right-handed individuals made up 44.24% of the combined population while the other 55.76% were unreported. These studies aimed to report the successful implementation of a BCI-robot system for hand rehabilitation and were more heterogeneous in terms of study and task designs than those studies that involved clinical testing. The most common approach was to design and implement a hand orthosis controlled by MI which accounted for 9 out of the 19 studies and were measured based on classification accuracy during the calibration/training period and online testing. Li et al. [73] and Stan et al. [79] also aimed to trigger a hand orthosis but instead of MI, the triggers used by Li et al. is based on an attention threshold while Stan et al. used a vision-based P300 speller BCI. Bauer et al. [82] compared MI against ME using a BCI-device while Ono et al. [85] studied the implementation of an action observation strategy with a combined visual and kinaesthetic feedback or auditory feedback. Five more studies [76,80,81,83,84] focused on varying the feedback while two more [74,86] assessed the performance and safety of a hybrid BCI with EMG, EOG or both.

For the studies that had a clinical testing component, a methodological quality assessment by the PEDro Scale was performed. Two studies which appeared on the PEDro search [60,65] had predetermined scores in the scale and were extracted for this part while the rest were manually evaluated by the authors. Table 5 shows the results of the methodological quality
assessment against the scale. Note that in the PEDro Scale, the presence of an eligibility criteria is not included in the final score.

Table 5. Methodological Quality of Clinical Studies based on PEDro Scale

| Criteria                              | Ang et al. | Barsotti et al. | Bundy et al. | Carino-Escobar et al. | Chowdhury-c | Frolov et al. | Norman et al. | Ono et al. | Tsushima et al. | Wang et al. |
|---------------------------------------|------------|-----------------|--------------|-----------------------|-------------|---------------|---------------|------------|-----------------|------------|
| 1 Eligibility criteria*               | 1          | 1               | 1            | 1                     | 1           | 1             | 0             | 1          | 1               | 1          |
| 2 Random allocation                   | 1          | 0               | 0            | 0                     | 0           | 0             | 1             | 0          | 0               | 1          |
| 3 Concealed allocation                | 0          | 0               | 0            | 0                     | 0           | 0             | 0             | 0          | 1               | 1          |
| 4 Baseline comparability              | 1          | 0               | 1            | 0                     | 1           | 1             | 0             | 0          | 0               | 0          |
| 5 Blind subjects                      | 0          | 0               | 0            | 0                     | 0           | 0             | 0             | 0          | 1               | 1          |
| 6 Blind therapists                    | 0          | 0               | 0            | 0                     | 0           | 0             | 0             | 0          | 0               | 1          |
| 7 Blind assessors                     | 1          | 0               | 0            | 0                     | 0           | 1             | 0             | 0          | 0               | 1          |
| 8 Adequate follow-up                  | 1          | 1               | 1            | 1                     | 1           | 0             | 1             | 1          | 1               | 1          |
| 9 Intention-to-treat analysis         | 0          | 0               | 1            | 1                     | 1           | 0             | 1             | 0          | 0               | 0          |
| 10 Between-group comparisons          | 1          | 0               | 0            | 0                     | 1           | 0             | 1             | 1          | 1               | 1          |
| 11 Point estimates and variability    | 1          | 1               | 1            | 1                     | 0           | 1             | 1             | 1          | 1               | 1          |
| **Total**                             | **6**      | **2**           | **4**        | **4**                 | **3**       | **5**         | **4**         | **3**      | **7**           | **7**      |

*not included in the final score
Discussion

To the best of our knowledge, this article was the first to compile BCI-driven robotic systems specific for hand rehabilitation. During this review, we found several limitations present among the studies collected and we examine these in more detail here and provide recommendations for future work in this area.

To provide clarity on the state-of-the-art and development of BCI-hand robot systems, we looked into the maturity of technology used in each study and determined by its readiness level (TRL). All but one in the prototype group was rated as having TRL 3 while the clinical group was more varied in their TRL (ranging from 5-7). The system used by Witkowski et al. [86], a prototype study, was rated TRL 4 due to the study being performed on the basis of improving and assessing its safety features. It is also worth noting that while a formal safety assessment was not performed for the TRL 3 prototypes of Stan et al. [79], Randazzo et al. [75] and Tacchino et al. [76], safety considerations and/or implementations were made; a criterion to be satisfied before proceeding to TRL 4. The system used by Chowdhury et al. is a good example of improving a TRL from 5 to 6 with a pilot clinical study published within the same year [63,64]. The two systems used in the RCT studies by Ang et al. [60] and Frolov et al. [65] achieved the highest score (TRL 7) among all of the studies which also meant that no BCI-hand robot system for stroke rehabilitation has ever been registered and commercially-released to date. This suggests that such systems lack the strong evidence that would propel commercialisation and technology adoption.

Heterogeneity in the study designs was apparent in both the clinical and prototype groups. The lack of control groups and random allocation in clinical studies (e.g., only 2 out of 7 studies are in the huge sample size RCT stage) made us unable to perform a meta-analysis of
effects and continue the study by Cervera et al [36] with a focus on BCI-hand robot interventions. Results from the methodological quality assessment showed that only two studies [68,69] had a score of 7 in the PEDro scale. Although non-conclusive, these results support the notion that most of the studies are not aligned with the criteria of high-quality evidence-based interventions. These factors also raise the need to develop clearly defined protocols when conducting BCI-hand robot studies on stroke patients. Until new systems have been assessed on this standard, it will be difficult to generate strong evidence supporting the effectiveness of BCI-robotic devices for hand rehabilitation.

In the development of any BCI-robotic device there are several design and feature considerations that need to be made to ensure that the systems are both fit for purpose and acceptable to the end-user. These design considerations must go beyond the scope of understanding the anatomy of the hand and the physiology of motor recovery in response to therapy. Feedback from stroke patients should be an essential part of this design process. The extracted studies, we surveyed the extent of end-user involvement in the initial stages of development (i.e., through consultations, interviews and therapy observations) and we found that there were no explicit statements about these in the reports. We recommend, as good practice, for future work in this area to report the type and degree of patient and/or physician involvement in device development to allow reviewers and readers to more readily gauge the potential usability of the system.

We were able to profile the BCI-hand robot systems regarding their technical specifications and design features. In hardware terms, a BCI-hand robot system involves three major components: (1) An EEG data acquisition system with several electrodes connected to a signal amplifier; (2) A computer where raw EEG data is received then processed by filters
and classifiers and where most of the cues and feedback during training is presented via a
visual display; (3) a robotic hand rehabilitation system for providing the physical therapy
back to the user.

The majority of the studies (N=19) used a BCI solely based on EEG while the rest were
combined with other sensors: EEG with EMG [60,63,72,76,80–83], EEG with force sensors
[64] and an EEG-EMG-EOG hybrid system [74,86]. The purpose of this integration is mainly
to improve signal quality by accounting for artefacts or to provide added modalities. Action
potentials such as those caused by ocular and facial movements interfere with nearby
electrodes and the presence of an added electrophysiological sensor accounting for these
would enable the technician to perform noise cancellation techniques as a first step in signal
processing. Almost all of the studies included used a standard EEG system with “wet”
electrodes (e.g., g.USBamp by g.tec and BrainAmp by Brain Products) while three used
Emotiv EPOC+, a semi-dry EEG system that uses sponge conductors infused with saline
solution. While the use of dry electrodes has been observed in pilot and prototype studies of
BCI-hand robot systems [52,49,78,87] and other motor imagery experiments [99–102], no
dry EEG system was used in the final 30 studies that tested healthy or stroke participants. It is
expected that as dry EEG systems continue to improve, their use in clinical studies of BCI
will also become increasingly prominent.

The degree of BCI-robotic control for the majority of the studies (N=26) was limited to
triggering the device to perform grasping (opening and closing of hand) and pinching (a
thumb-index finger pinch or a 3-point thumb-index-middle finger pinch) movements using
MI and other techniques. This means that no robotic control setup among the screened studies
were able to perform digit-specific MI. This is a limitation caused by the non-invasive setup
of EEG and is due to the low spatial resolution brought by the distances between electrodes [103]. The homunculus model, a representation of the human body in the motor strip, maps the areas of the brain where activations have been reported to occur for motor processes. The challenge of decoding each finger digit MI in one hand is that they only tend to occupy a small area in this strip. Hence even the highest resolution electrode placement system (i.e., the five percent or 10-5 system – up to 345 electrodes) would have difficulties accounting for digit-specific MI for BCI. In contrast to EEG, electrocorticography (ECoG) have been used to detect digit-specific MI. The electrodes of ECoG come in contact directly with the motor cortex and is an invasive procedure; making it non-ideal for use in BCI therapy [104]. It is worth noting however that some studies were successful in implementing continuous control based on ERD/ERS patterns: Bundy et al. [62] and Norman et al. [67] were able to apply continuous control of a 3-DOF pinch-grip exoskeleton based on spectral power while Bauer et al. [82] provided ERD-dependent control of finger extension for an end-effector robot. These continuous control strategies have been shown to be very useful in BCI-hand robots for assistive applications (i.e., partial or full device dependence for performing ADL tasks [105]). Whether this type of control can significantly improve stroke recovery is still in question as the strategy of robots for stroke rehabilitation can be more classified as a therapeutic “exercise” device.

Signal processing and machine learning play a vital role in the development of any EEG-based BCI. The pre-processing techniques (e.g., filtering, artefact removal), types of features computed from EEG, and the classifier used in machine learning can significantly affect the performance of the robotic system in classifying the user’s intent via MI [106]. This systematic review has revealed that approaches to develop MI EEG-based BCI are highly diverse in nature, which makes it difficult to compare across the systems and hinders the
development of new BCI systems informed by the strengths and weaknesses of existing state-of-the-art systems. The diversity in the design process can be beneficial to develop complex MI EEG-based BCI systems to achieve high efficiency and efficacy. However, such newly developed systems should be open sourced and easily reproducible by the research community to provide valid performance comparisons and drive forward the domain of robotic-assisted rehabilitation.

In addition to MI, other strategies for robotic control were reported. Diab et al. [88] and King et al. [89] both facilitated the movements of their respective orthoses by physical practice while Stan et al. [79] utilised a P-300 evoked potential speller BCI, where the user visually focused on a single alphanumerical character situated in a grid. The chosen character then corresponded to a command for the hand orthosis thereby producing the desired stimulus for the patient. While the latter study reported 100% accuracy rate in terms of intention and execution, the EEG channels were situated in the visual cortex rather than the motor strip which deviates from the goal of stimulating the desired brain region for plasticity.

In order to facilitate hand MI and account for significant time-points in the EEG data, all the studies employed a cue-feedback strategy during their trials. 19 of the studies presented a form of visual cue while the rest, except for two unspecified [69,87], involved cues in auditory (“bleep”) [76,80–83], textual [78,79,89] or verbal [88] forms. As for the provision of a matching sensory feedback, 16 studies presented a combination of kinaesthetic and visual feedback with some also providing auditory feedback during successful movement attempts. All the studies provided kinaesthetic feedback through their robotic devices. Some systems with visual feedback, such as Wang et al. [68], Li et al. [73], Chowdhury et al. in both of their clinical studies [63,64] and Ono et al. in their clinical [66] and pilot testing experiments [85],
used a video of an actual hand performing the desired action. Ang et al. [60] and Stan et al. [79], in a different strategy, provided visual feedback through photo manipulation and textual display, respectively. While the latter two studies reported promising results (with Ang et al. in RCT stage and Stan et al. having 100% classification accuracy), it should also be considered that such cue and feedback types (including Graz visualisations and auditory forms) are non-representative of hand movement and may not provide the same stimulation as a geometrical representation of a hand moving its desired course. This may be essential when we base principles of stroke recovery in alignment with how MI correlates with AO – an underlying theme of the motor simulation theory proposed by Jeannerod [15]. Figure 4 shows how different kinds of visual cue and feedback can be presented to participants to help facilitate MI.

**Figure 4.** Visual cue and feedback during MI trials in different conditions. (a) Graz MI visualisations, (b) video recordings of hand movement and (c) virtual hand representation through VR/AR.
Future Directions

There is clearly great potential for the use of BCI-hand robots in the rehabilitation of an affected hand following stroke. Nevertheless, it is important to emphasise that there is currently no solid evidence to support the use of such systems within clinical settings. Moreover, the purported benefits of these systems rest on conjectures that require empirical evidence. In other words, there are grounds for supposing that MI could be useful within these rehabilitation settings but no supporting evidence. This systematic review has also revealed that there are a number of technological limitations to existing BCI-hand robotic systems. We stress an urgent need to address these limitations to ensure that the systems meet the minimum required levels of product specification (in measuring brain activity, processing signals, delivering forces to the hand and providing rich feedback and motivating settings). We question the ethics or usefulness of conducting clinical trials with such systems until they can demonstrate minimum levels of technological capability. We consider below what standards these systems should obtain before subjecting them to a clinical trial and discuss might constitute an acceptable standard for a clinical trial.

Ideal Setup for a BCI-hand Robot

We summarise the information revealed via the systematic review about what constitutes an acceptable setup for a BCI-hand robot for stroke rehabilitation. We focus on improving individual components in data acquisition, data processing, the hand rehabilitation robot, and the visual cue and feedback environment. Table 6 presents the features and specifications of a fully integrated acceptable system.
Table 6. Exemplary Features and Specifications of Future BCI-Hand Robot Systems

| Component                      | Features and Specifications                                                                 |
|--------------------------------|------------------------------------------------------------------------------------------|
| Data Acquisition System and Software | • Dry EEG system with 8-16 channels, comfortable and easy to use                        |
|                                 | • Inclusion of other bio-signal sensors such as EMG, EOG, force, accelerometers to remove artefacts and improve classification |
|                                 | • Robust and reliable signal processing software: machine learning-based algorithms that discriminate brain states such as MI or evoked potentials and have lower calibration times |
| Hand Robot                      | • Safe, comfortable and aligned with the hand’s range of motion                           |
|                                 | • Effective in providing kinaesthetic feedback                                           |
|                                 | • Use of back-drivable or soft actuators that effectively assist movement without additional injury |
|                                 | • Multiple levels of safety and emergency features (mechanical, electronic, software), clear and obvious operation |
| Visual Cue and Feedback         | • Provide rich visual cue and feedback to intended tasks, geometric representation of the hand (video or simulated environment), can be in multiple platforms such as display monitors or VR/AR headsets |
|                                 | • Gamification of therapy exercises to provide an engaging regime to stroke patients      |

The implementation of these features in an ideal BCI-robot setup needs to be weighed against socioeconomic factors in healthcare delivery for it to be considered market ready. An ideal BCI system should provide above chance-level classification (>60%) after the first session on the first day of therapy. Ideally, the classification algorithm should also translate to following sessions or days; reducing the number of training sessions and focusing on the main therapy tasks. An alternative approach is to focus on making the setup an engaging experience. In other words, the delivery of intervention can be started immediately the patient wears the EEG cap and runs the BCI system. For the hand robot system, more straightforward criteria
can be followed with the existence of the numerous design protocols, regulation standards and assessment matrices mentioned in this review. Nevertheless, end-user involvement in the design with the prioritisation of safety while allowing the most natural hand movement and ROM as possible is the recommended goal.

**Ideal Setup for Clinical Trials**

We also propose a set of specialised criteria for BCI-hand robot systems in addition to the standard motor improvement scores (e.g. ARAT, FMMA) evaluated during clinical trials. Firstly, classification accuracies between intended and interpreted actions from the data acquisition and software component should always be accounted to track the effectiveness of BCI in executing the clinical task. In addition to this, system calibration and training procedures, especially its duration, should be detailed in the protocol to document the reliability of the classification algorithm. There is not much to consider in the use of robotic devices as they are most likely to be mature (if not yet commercially available) before being used as the hardware component in the study. However, the devices’ functionality (i.e., task to be performed, degree of control and motion, actuation and power transmission etc.) should always be stated as they contribute to the evaluation of interactions between other components in the system. Lastly, controls for the clinical study must always be included, even with small-scale patient studies. As discussed in this article, these controls may be in the form of sham, standard arm therapy (SAT), standard robotic therapy, congruency feedback and quality of stimuli among others. Having regarded and implemented these criteria would help homogenise the clinical data for future meta-analyses, strengthen evidence-based results and provide a reliable way of documentation for individual and/or interacting components.
Proposed roadmap

We suggest that the immediate focus for BCI-controlled robotic device research should be around the engineering challenges. It is only when these challenges have been met that it is useful and ethical to subject the systems to clinical trials. We recommend that the challenges be broken down into the following elements: (1) data acquisition; (2) signal processing and classification; (3) robotic device; (4) priming and feedback environment; (5) integration of these four elements. The nature of these challenges means that a multidisciplinary approach is required (e.g. the inclusion of psychologists, cognitive neuroscientists and physiologists to drive the adoption of reliable neural data acquisition). It seems probable that progress will be made by different laboratories tackling some or all of these elements and coordinating information sharing and technology improvements. Once the challenges have been met (i.e. there is a system that is able to take neural signals and use these to help drive a robotic system capable of providing appropriate forces to the hand within a motivating environment) then robust clinical trials can be conducted to ensure that the promise of this approach does translate into solid empirical evidence supporting the use of these systems within clinical settings.
Conclusions

Research on BCI-controlled robotic devices for hand rehabilitation after stroke is a rapidly growing field and is gaining traction in the academic and medical research communities. The three main objectives of this systematic review were: (1) to survey how BCI technologies are utilised in controlling robotic devices for hand rehabilitation, (2) to determine the state-of-the-art developments in BCI systems in terms of hand MI resolution and degree of robotic control, and (3) to assess the clinical significance of BCI-hand robot systems by accounting clinical studies with outcome measures relating to motor recovery. Here, we were able to address these three and provide insight on the future of BCI-controlled robotics for stroke therapy.

We surveyed 30 EEG-based BCI-hand robot systems designed for stroke with majority of the studies (N=19) in their prototype development and pilot testing stages having TRL scores of 3-4. The rest of the studies (N=11) involved a clinical component into it, having tested on stroke patients. The systems used in the clinical group were rated with the highest technological readiness: TRL 7 for two studies undergoing RCT. Profiling the EEG acquisition systems confirmed the still dominance of standard EEG systems that uses “wet” electrodes over the recent dry electrode systems. However, as the latter’s technology continues to improve in the next years, we may see a positive shift towards these techniques in terms of usage and preference. The common goal among these studies is to successfully discriminate and with high accuracy a user’s intent via motor imagery. While most have reported reliable, above chance-level accuracy rates, we observe the limitations evident in hand motor imagery resolution (e.g., intention to grasp or pinch as opposed to rest, discriminating from left and right movement, signal processing techniques) and the degree of robotic control (i.e., triggering and continuous control). The task designs, cues and matching
sensory feedback modes play an important role in motor imagery ability. We give attention to
the inferior visual stimuli presented in most of the trials and suggest the use of a rich and
engaging one through the different immersive platforms such as Virtual Reality and
Augmented Reality. We also report that the clinical adoption of BCI-hand robots is still in its
infancy due to few studies reporting significant improvements in the functional recovery of
stroke patients. We suggest the development of a standard protocol in assessing clinical
outcomes as an effort to strengthen the argument that these systems are not only
economically feasible but also viable and robust for the therapy of motor impairment post-
stroke.

Finally, we recommend that future developers focus on end-user involvement in the early
design stages, achieving the successful integration of the individual components and making
the system as safe and cost-effective as possible without compromising on reliability and
robustness. These steps should allow this promising technology to advance, be adopted by the
stakeholders and improve the quality of life for stroke survivors.
### List of Abbreviations

| Code | Abbreviation                  | Description                                      |
|------|-------------------------------|--------------------------------------------------|
| ADL  | Activities of Daily Living    |                                                  |
| ANN  | Artificial Neural Network     |                                                  |
| AO   | Action Observation            |                                                  |
| AR   | Augmented Reality             |                                                  |
| ARAT | Action Research Arm Test      |                                                  |
| BCI  | Brain-Computer Interface      |                                                  |
| BMI  | Brain-Machine Interface       |                                                  |
| CDRH | Center for Devices and Radiological Health |                                |
| CSD  | Covariate Shift Detection     |                                                  |
| CSP  | Common Spatial Pattern        |                                                  |
| DC   | Direct Current                |                                                  |
| ECoG | Electrocorticography          |                                                  |
| EEG  | Electroencephalography        |                                                  |
| EMG  | Electromyography              |                                                  |
| EOG  | Electrooculography            |                                                  |
| ERD  | Event-Related Desynchronisation |                                              |
| ERP  | Event-Related Potential       |                                                  |
| ERS  | Event-Related Synchronisation |                                                  |
| ERSP | Event-Related Spectral Perturbation |                                        |
| FBCSP| Filter Bank Common Spatial Pattern |                                    |
| FIR  | Finite Impulse Response       |                                                  |
| FMMA | Fugl-Meyer Motor Assessment   |                                                  |
| GS   | Grip Strength                 |                                                  |
| IIR  | Infinite Impulse Response     |                                                  |
|   | Acronym | Description                                           |
|---|---------|-------------------------------------------------------|
| 692| LDA     | Linear Discriminant Analysis                          |
| 693| ME      | Motor Execution                                       |
| 694| MI      | Motor Imagery                                         |
| 695| PEDro   | Physiotherapy Evidence Database                       |
| 696| PMA     | Premarket Approval                                    |
| 697| PRISMA  | Preferred Reporting Items for Systematic Reviews and Meta-Analysis |
| 698| PROSPERO| International Prospective Register of Systematic Reviews |
| 699| PS      | Pinch Strength                                        |
| 700| QSR     | Quality System Requirement                            |
| 701| RCT     | Randomised Clinical Trial                             |
| 702| SAT     | Standard Arm Therapy                                  |
| 703| SVM     | Support Vector Machine                                |
| 704| TRA     | Technology Readiness Assessment                       |
| 705| TRL     | Technology Readiness Levels                           |
| 706| UK-MRC  | United Kingdom Medical Research Council               |
| 707| VR      | Virtual Reality                                       |
**Declarations**

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**Availability of Data and Materials**

A full database of selected studies including those extracted during the search and selection process is available from the corresponding author on reasonable request.

**Authors’ Contributions**

PDEB and ECS performed the initial search and screening of the studies. MA performed the analysis of signal processing techniques. AA, AEJ and RJH made contribution to the robotics, design and other engineering aspects of the current work. FM provided analysis related to EEG and BCI. MMW contributed to the clinical and overall direction of the review. PDEB, FM and MMW were the major contributors to the writing of the manuscript. All authors read and approved the final manuscript.

**Competing Interests**

The authors declare that they have no competing interests.

**Ethics Approval and Consent to Participate**

Not applicable.
Consent for Publication

Not applicable.

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Table 2. Summary of Studies

| Authors            | Participants | Study Design                                      | Task Design                                                                 | BCI-Hand Robot                                                                 | Main Outcomes                                                                 |
|--------------------|--------------|---------------------------------------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Ang et al., 2014   | N=27 (7F:14M)| 3-armed RCT of motor function with MI-BCI-device as intervention | Photo manipulation: hand opening and closing, pronation and supination       | EEG: 27 channels to classify ERD/ERS and coupled with EMG to confirm MI       | Clinical outcome measure: FMMA Distal, improvement in weeks 3, 6, 12, 24       |
|                    | Moderate to severe impairment of UE function      | Control groups: device only (Haptic Knob), SAT                               | Cue: visual (photo)                                                          | Device: Haptic Knob, 2-DOF for hand grasping and knob manipulation           | BCI-device group = 2.5±2.4, 3.3±2.3, 3.2±2.7, 4.2±3.1                      |
|                    | Mean age: 54.2y                                    | Feedback: visual (photo) and kinaesthetic                                    | Minimum time required to perform MI = 2s                                     | Actuation: DC brushed motors with linear belt drive                          | Device only group = 1.6±2.5, 2.9±3.0, 2.5±2.6, 2.5±3.0                   |
|                    | Mean stroke duration: 385.1 days                   |                                                                                  | Control: trigger                                                             | SAT group = 0.4±1.1, 1.9±1.9, 1.0±1.3, 0.3±2.1                              |                                                                                 |
| Barsotti et al.,   | N=3 (1F:2M) | Probing MI classification by BCI training, time-frequency analysis and robot trajectories | Reaching-grasping-releasing                                                  | EEG: 13 channels to classify ERD                                             | Mean classification accuracy during BCI training = 82.51±2.04%               |
| 2015               | Chronic stroke survivors with right arm hemiparesis| Uncontrolled                                                                  | Cue: visual                                                                 | Device: BRAVO 2-DOF hand orthosis attached to full UE exoskeleton           | Average delay from visual cue to robot initiation = 3.45±1.6s               |
|                    | Mean age: 62±12y                                   | Feedback: kinaesthetic                                                        | Minimum time required to perform MI = 2s                                     | Actuation: DC motors with rigid links                                       | Average delay due to patient’s ability to start MI = 1.45s                  |
| Bundy et al.,      | N=10                                                 | Motor function evaluation before and after intervention by MI-BCI from unaffected hemisphere | Opening of affected hand                                                    | EEG: 8 channels to classify ERD                                              | Clinical outcome measure: ARAT Score, improvement from baseline to completion (12 weeks) |
| 2017               | Chronic hemiparetic stroke with moderate to severe UE hemiparesis | Uncontrolled                                                                | Cue: visual                                                                 | Device: 3-pinch grip, 1-DOF hand exoskeleton                               | Mean ± SD = 6.20±3.81                                                      |
|                    | Mean age: 58.6±10.3y                                | Feedback: visual and kinaesthetic                                              |                                                                           |                                                                                  |                                                                                 |
| Study                        | N=         | Patient Characteristics                                                                 | Intervention Details                                                                 | Control                                                                 | Note                                                                 |
|------------------------------|------------|----------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|------------------------------------------------------------------------|----------------------------------------------------------------------|
| Bundy et al. (cont’d)        |            |                                                                                        |                                                                                      | Control: continuous depending on spectral power                        | Note: 5.7 ARAT Score is the minimal clinically important difference in chronic stroke survivors |
| Carino-Escobar et al. 2019 [70] | 9 (4F:5M) | Subacute ischaemic stroke Mean age: 59.9±2.8y Mean stroke duration: 158(±74)-185(±73) days | Determine longitudinal ERD/ERS patterns and functional recovery with BCI-robot Uncontrolled Extension-flexion of hand fingers Cue: visual (Graz MI) Feedback: visual and kinaesthetic | EEG: 11 channels to classify ERD/ERS Device: hand finger orthosis Actuation: DC motor with screw system for linear displacement, flexible links Control: trigger | FMA-UE: N=3 reported equal or higher than 3 score gains, N=3 no score gains, Mean longitudinal ERD/ERS: beta bands have higher association with time since stroke onset than alpha, and strong association with UL motor recovery |
| Chowdhury et al., 2018-b [63] | 20        | 10 healthy and 10 hemiplegic stroke patients Mean age (healthy, stroke): 41±9.21y, 47.5±14.23y | Probe non-adaptive classifier (NAC) vs. Covariate Shift adaptive classifier (CSAC) of MI in EEG Extension-flexion of hand fingers Cue: visual Feedback: visual and kinaesthetic | EEG: 12 channels with EMG to classify ERD/ERS Device: EMOHEX 3-finger, 3-DOF each, exoskeleton (thumb, index, middle) Actuation: servomotors with rigid links Control: trigger | Mean classification accuracies during BCI training: Healthy group: calibration = 78.50±9.01%, NAC = 75.25±5.46%, CSAC = 81.50±4.89% Patient group: calibration = 79.63±13.11%, NAC = 70.25±3.43%, CSAC = 75.75±3.92% |
| Chowdhury et al., 2018-c [64] | 4 (2F:2M) | Hemiplegic stroke patients, right-handed, left hand impaired Mean age: 44.75±15.69y Mean stroke duration: 7 ±1.15mo | Motor function evaluation by using active physical practice followed by MI-BCI-controlled device intervention Extension-flexion of hand fingers Cue: visual Feedback: visual and kinaesthetic | EEG: 12 channels with force sensors to classify ERD/ERS Device: EMOHEX 3-finger, 3-DOF each, exoskeleton (thumb, index, middle) Actuation: servomotors with rigid links Control: trigger | Classification accuracies of 4 participants: P01 = 81.45±8.12%, P02 = 70.21±4.43%, P03 = 76.88±4.49%, P04 = 74.55±4.35% Clinical outcome measures: GS and ARAT Scores, improvement from baseline to completion (6 weeks) GS scores: group mean difference = +6.38 kg, p=0.06 |
| Study | Year | Methodology | Participants | Procedure | Outcome Measures |
|-------|------|-------------|--------------|-----------|-----------------|
| Chowdhury et al., 2018 | | Multi-centre RCT of MI-BCI-controlled hand exoskeleton | N=74 (26F:48M) | 3 Tasks: (1) motor relaxation, (2) imagery of left-hand opening, (3) imagery of right-hand opening | ARAT scores: group mean difference = +5.66, p<0.05 |
| Frolov et al., 2017 [65] | | Subacute or chronic stroke with mild to hemiplegic hand paresis, right-handed | N=74 (26F:48M) | EEG: 30 channels to classify the three mental tasks by Bayesian classifier based on covariance matrices | Mean classification accuracy during BCI training = 40.6% |
| Norman et al., 2018 [67] | | Cortical and subcortical single haemorrhagic or ischaemic stroke (at least 6 months) | N=8 (All male) | EEG: 16 channels mapping SMR changes | Mean classification accuracies: 8 participants: 83.1%, 76.3%, 73.3%, 68.2%, 74.5%, 86.5%, 47.9%, 40.0% |
| Ono et al., 2016-a [66] | | Chronic stroke patients with hemiplegic hands | N=21 (9F:12M) | EEG: 9 channels to classify ERD | Mean classification accuracies: Congruent feedback = 56.8±5.2%, chance level=36.4±4.5% |

**Mean age:**
- Frolov et al., 2017: 59.5±11.8y
- Norman et al., 2018: 59.5±11.8y
- Ono et al., 2016-a: 57.9±2.4y
| Authors                  | Participants | Study Design | Task Design | BCI-Hand Robot | Main Outcomes                                                   |
|-------------------------|--------------|--------------|-------------|----------------|----------------------------------------------------------------|
| Ono et al., 2016-a      | N=18 (3F:14M) Chronic haemorrhagic or ischaemic stroke (from 2mo onwards) | Implementation of MI-controlled robotic orthosis as neurofeedback | Extension of hand finger | Actuation: pneumatic motors with rigid links | Significant time-intervention interaction in the ipsilesional sensorimotor cortex. Higher coactivation of sensory and motor cortices for neurofeedback group in the ipsilesional sensorimotor cortices as compared to SHAM |
|                         | Mean age: 58±10y | | Cue: unspecified | Control: trigger | | |
|                         |              |              | Feedback: kinaesthetic and electrical stimulation | | | |
| Tsuchimoto et al., 2019 | N=24 (4F:20M) Chronic stroke patients with paralysed hands | Implementation of action observation and motor imagery (AO+MI) with kinaesthetic feedback | Hand grasping | EEG: 5 channels to classify MI | AO+MI with kinaesthetic feedback group showed significant improvements in FMA-UE across longitudinal evaluation [$\chi^2(2) = 7.659, p = 0.022$], no significant difference in SHAM group [$\chi^2(2) = 4.537, p = 0.103$] |
| [69]                    | Mean age: 54±9y | | Cue: visual (video of hand action / textual cues in SHAM group) | Device: robotic finger orthosis | | |
|                         |              |              | Feedback: visual and kinaesthetic | Actuation: servo motors with rigid links | | |
|                         |              |              | | Control: trigger | | |
| Wang et al., 2018       | N=20 (11F:9M) Right-handed | Study on MI as compared to motor execution (ME) using BCI-device | Opening of left hand | EEG: 31 channels to detect ERD, with EMG to classify MI from execution and account for tonic contraction | Principal component analyses (between MI and execution) generated coefficients for the visual (VIS) and kinaesthetic (KIS) imagery scale, BCI-robot performance (BRI), tonic contraction task (MOC) and visuomotor integration task (VMI). VIS and KIS yielded high coefficients on MI while MOC and VMI yield high coefficients on ME. BRI show high coefficient yields on both MI and ME. |
| [68]                    | Mean age: 28.5±10.5y | | Cue: auditory | Device: Amadeo, Tyromotion, Austria | | |
|                         |              |              | Feedback: kinaesthetic | Control: discontinuation of ERD stops finger extension | | |
| Study                              | Authors                                      | N   | Design and implementation of | Cue: | Feedback: | EEG: | Device: | Actuation: | Control: | Correctly classified trials | Comments                                      |
|-----------------------------------|----------------------------------------------|-----|------------------------------|------|-----------|------|---------|-------------|----------|-----------------------------|-----------------------------------------------|
| Cantillo-Negrete et al., 2015[72] | Cantillo-Negrete et al.                      | 1   | Design and implementation of  | visual | kinaesthetic | 11   | 1-DOF hand | DC motor   | trigger | 78%                         |                                               |
|                                   |                                              |     | a MI-controlled hand orthosis| (modified Graz) |            |       | finger orthosis | with screw system for linear displacement, flexible links |        |                                                                      |
|                                   |                                              |     | Extension-flexion of         |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | right-hand finger            |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | of right-hand finger         |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | Extension-flexion of         | visual |            |      |         |             |          |                                                                      |
|                                   |                                              |     | of right-hand finger         |       |           |      |         |             |          |                                                                      |
| Chowdhury et al., 2015-a[73]      | Chowdhury et al.                             | 6   | Study of cortico-muscular     | visual | kinaesthetic | 10   | EMG      | servomotors with rigid links |         | 69.17%, 71.25%, 67.92%   | Mean classification accuracies: passive execution = 69.17%, hand execution = 71.25%, MI = 67.92% |
|                                   |                                              |     | coupling in robotic finger   |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | exoskeleton control          |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | Extension-flexion of         | visual |            |      |         |             |          |                                                                      |
|                                   |                                              |     | of right-hand finger         |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | Extension-flexion of         | visual |            |      |         |             |          |                                                                      |
|                                   |                                              |     | of right-hand finger         |       |           |      |         |             |          |                                                                      |
| Coffey et al., 2014[74]          | Coffey et al.                                | 3   | Design and implementation of  | visual | kinaesthetic | 27   | Arduino  | pneumatic   |         | Glove inflation-deflation cycle = 22s | Classification accuracies of 3 participants: A = 92.5%, B = 90.0%, C = 80.0% |
|                                   |                                              |     | a MI-controlled hand orthosis|       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | Hand digit and wrist         | visual |            |      |         |             |          |                                                                      |
|                                   |                                              |     | contraction and              | (Graz MI) |            |      |         |             |          |                                                                      |
|                                   |                                              |     | extension                    |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | Extension-flexion of         | visual |            |      |         |             |          |                                                                      |
|                                   |                                              |     | of right-hand finger         |       |           |      |         |             |          |                                                                      |
| Diab et al., 2016[75]            | Diab et al.                                  | 5   | Design and implementation of  | verbal | kinaesthetic | 14   | actuated Talon | linear     |         | Mean classification accuracies: simulation studies = 95%, online BCI training = 86% |                                               |
|                                   |                                              |     | EEG-triggered wrist          |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | orthosis with accuracy       |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | improvement                  |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | Hand opening and closing     | verbal instruction |            |      |         |             |          |                                                                      |
|                                   |                                              |     | EEG: 14 channels to detect   | verbal instruction |            |      |         |             |          |                                                                      |
|                                   |                                              |     | hand movement-related EEG    |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | Device: actuated Talon wrist |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | orthosis                    |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | Actuation: linear            |       |           |      |         |             |          |                                                                      |
|                                   |                                              |     | Control: trigger             |       |           |      |         |             |          |                                                                      |


| Study              | Participants | Design and Implementation | Cue | Feedback | EEG Channels | Device | Actuation | Control | Mean Classification Accuracy | Offline Classification Accuracy |
|--------------------|--------------|---------------------------|-----|----------|--------------|--------|-----------|---------|-------------------------------|--------------------------------|
| Fok et al., 2011   | N=4          | Design and implementation of a MI-controlled hand orthosis | Hand opening and closing | unspecified | EEG: 14 channels to detect MI-related ERD | Device: actuated Talon wrist orthosis | Actuation: linear actuator | Control: trigger | EEG signals from imagined hand movement was correlated with the contralesional hemisphere and utilised to trigger the actuation of orthosis | ERD was detected from 12 Hz bin power of EEG during move condition |
| Li et al., 2019    | N=14 (4F:10M) Mean age: 23.8±0.89y | Design and implementation of an attention-controlled hand exoskeleton with rigid-soft mechanism | Hand grasping | visual (video of hand action) | EEG: 3 channels to map signals relative to attention | Device: hand exoskeleton | Actuation: linear actuator with rigid-soft mechanism | Control: Trigger | Mean classification accuracy: 95.54% actuation success rate against the attention threshold | |
| Holmes et al., 2012 | N=6 (All male, young adults) | Design and implementation of a MI-controlled hand orthosis | Hand opening and closing | textual | EEG: 14 channels to detect hand movement-related EEG | Device: ExoFlex Hand Exoskeleton controlled by Arduino | Actuation: linear actuator connected to chained links that flex | Control: trigger | Classification accuracies of 6 participants: T001 = 95%, T002 = 98%, D001 = 91%, U001 = 93%, E001 = 87%, E002 = 86% | |
| King et al., 2011  | N=1 (Female) 24y | Contralateral control of hand orthosis using EEG-based BCI | Right hand idling and grasping | textual | EEG: 63 channels to control contralateral hand movement | Device: hand orthosis | Offline classification accuracy = 95.3±0.6%, p < 3.0866×10⁻²⁵ | Average lag from voluntary contractions to BCI-robot control = 2.24 ± 0.19s (after 5 sessions) | |
| Study                  | Participants | Design/Feedback | Actuation | Control |
|-----------------------|--------------|----------------|-----------|---------|
| King et al. (cont’d)  |              | Actuation: servomotors attached to Bowden cables as tendons | Control: trigger |
| Naros et al., 2016    | N=32 (16F:16M) Mean age: 25.9±0.5y | 2x2 factorial design with parameters: adaptive classifier threshold and non-adaptive classifier threshold, contingent feedback and non-contingent feedback | Opening of right hand | EEG: 32 channels to detect ERD, with EMG to classify MI (FC3, C3, CP3 used) |
|                       |              | Cue: auditory Feedback: kinaesthetic | Device: Amadeo, Tyromotion, Austria | Control: trigger |
|                       |              | Significant enhancement in group 1 (adaptive classifier + contingent feedback), p=0.0078 | | |
|                       |              | Significant reduction in group 4 (non-adaptive classifier + non-contingent feedback), p=0.0391 | | |
|                       |              | Motor performance improvement over baseline from first and last tasks, significant results: | | |
|                       |              | Group 1 (adaptive classifier + contingent feedback), p=0.0313 | | |
|                       |              | Group 4 = (non-adaptive classifier + non-contingent feedback), p=0.0411 | | |
| Ono et al., 2018-b    | N=28 Right-handed except 1 | Implementation of an action observation strategy with visual and proprioceptive, or auditory feedback to MI | Opening of right hand | EEG: 9 channels to classify ERD |
|                       |              | Cue: visual (video of hand performing action) Feedback: visual, kinaesthetic and auditory | Device: Power Assist Hand - Team ATOM, Atsugi, Japan | |
|                       |              | AO+MI + proprioceptive and visual feedback: | Actuation: pneumatic motors with rigid links | |
|                       |              | Mean MI-ERD powers of correct feedback vs SHAM provide significant interaction, F_{1,17}=6.618, p=0.020 (6 days) Mean classification accuracies: 100% (on 6th letter flash during calibration) | Control: trigger |
|                       |              | Statistically significant increase in MI-ERD power in correct feedback group over baseline, p=0.012 (6 days) | | |
| Stan et al., 2015     | N=9          | Trigger a hand orthosis using a P300 speller BCI | Spell E (enable), A (hand opening) and B (hand closing) in P300 speller BCI to perform hang grasping, moving and releasing objects | EEG: 8 channels focusing on visual cortex |
|                       |              | Cue: textual (spelling) | Device: hand orthosis | |
|                       |              | Actuation: 2 servomotors and | Actuation: hand orthosis |
|                       |              | | |
| Study                                      | Participants | Details |
|--------------------------------------------|--------------|---------|
| Stan et al. (cont’d)                       |              |         |
| Ramos-Murguialday et al., 2012 [83]        | N=23         | Mean age (contingent positive, contingent negative, SHAM): 26.6±4y, 26.5±5y, 26.2±2y |
|                                            |              | Probing MI with proprioceptive feedback |
|                                            |              | Experimental groups: contingent positive, contingent negative feedback |
|                                            |              | Control group: SHAM |
|                                            |              | 5 tasks: MI without direct control, MI with direct control, passive, active, rest |
|                                            |              | Cue: auditory |
|                                            |              | Feedback: visual and kinaesthetic |
|                                            |              | Control: trigger |
|                                            |              | EEG: 61 channels with EMG to classify ERD/ERS |
|                                            |              | Device: hand orthosis |
|                                            |              | Actuation: DC motor M-28 with a worm gearhead and Bowden cables for each finger |
|                                            |              | Contingent positive feedback provided higher BCI performance during MI without feedback than contingent negative and SHAM; and higher during MI with or without feedback as compared to rest |
| Ramos-Murguialday and Birbaumer, 2015 [84] | N=9          | Right-handed Mean age: 26.6±4y |
|                                            |              | Detect oscillatory signatures of motor tasks during EEG |
|                                            |              | 5 tasks: MI without direct control, MI with direct control, passive, active, rest |
|                                            |              | Cue: auditory |
|                                            |              | Feedback: visual and kinaesthetic |
|                                            |              | Control: trigger |
|                                            |              | EEG: 61 channels with EMG to classify ERD/ERS |
|                                            |              | Device: hand orthosis |
|                                            |              | Actuation: DC motor M-28 with a worm gearhead and Bowden cables for each finger |
|                                            |              | Significant change in power in all frequency ranges during MI with direct control before trial initiation |
|                                            |              | Kinaesthetic feedback increased significant changes in alpha and beta power; therefore, increasing BCI performance |
| Randazzo et al., 2018 [85]                | N=9 (2F:7M)  | Mean age: 23±5y |
|                                            |              | Design and implementation of a hand orthosis with testing of kinaesthetic effects in EEG |
|                                            |              | 4 tasks: rest (REST), exoskeleton-induced hand motions (EXO), MI of right hand (MI), exoskeleton-induced hand motions plus MI (MIEXO) |
|                                            |              | Cue: visual |
|                                            |              | Feedback: kinaesthetic |
|                                            |              | Control: passive (exoskeleton not dependent on MI to |
|                                            |              | EEG: 16 channels to detect MI |
|                                            |              | Device: mano hand exoskeleton |
|                                            |              | Actuation: linear servomotors attached to Bowden cables as tendons |
|                                            |              | Mean classification accuracies among groups: |
|                                            |              | (vs REST) MI = 63.02±5.91%, EXO = 69.64±5.74%, MIEXO = 72.19±6.57% |
|                                            |              | MIEXO vs EXO = 69.91±9.86% |
|                                            |              | Chance level at 95% confidence = 58% (N=50 trials) |
| Study                  | N   | Gender | Mean age | Task Description                                                                 | Design                           | EEG Channels | Device                        | Feedback                          | Controls                                        | Findings                                                                                     |
|------------------------|-----|--------|----------|---------------------------------------------------------------------------------|----------------------------------|-------------|-------------------------------|-----------------------------------------------|------------------------------------------------|--------------------------------------------------------------------------------------------|
| Randazzo et al. (cont’d) |     |        |          | Move during MI EXO task)                                                        | 2x2 factorial design             | 19          | Gloreha hand rehabilitation   | Auditory and kinaesthetic                    | Passive (glove not dependent on brain state during tasks) | Statistically significant ERD changes in beta and mu bands were observed to initiate earlier in tasks A and C (involves active movement) |
| Tacchino et al., 2017  | 8   | 7F:1M  | 26.3±1.9y| Opening and closing of hand, 4 tasks: (A) glove with active movement, (B) glove with passive movement, (C) no glove with active movement, (D) no glove and no movement | N=8                              | 2x2          | Gloreha hand rehabilitation   | Auditory and kinaesthetic                    | Passive (glove not dependent on brain state during tasks) | Stronger and longer ERD was observed in tasks A and B (involves robotic assistance) suggesting reinforced afferent kinaesthetic feedback |
| Vukelic and Gharabaghi, 2015 | 11  | 4F:7M  | 25.83±3.1y| Assessment sensorimotor activity during MI with either visual or kinaesthetic feedback | N=11                             | 2x2          | Amadeo, Tyromotion, Austria | Auditory and kinaesthetic (separated by experimental groups) | Trigger MI + kinaesthetic feedback group resulted in higher beta ERS (p=0.02) during rest and higher beta ERD (p=0.04) during MI | Kinaesthetic feedback provides higher stability and sustained beta ERD activity than visual feedback |
| Witkowski et al., 2014  | 12  | 4F:8M  | 28.1±3.63y| Assessment performance and safety of EEG-EOG hybrid BCI                          | N=12                             | 2x2          | HX hand exoskeleton           | Kinaesthetic                                    | Trigger Mean classification accuracies: | Mean classification accuracies: |
|                        |     |        |          | Right hand opening                                                              |                                   | 128         | Electric actuators with Bowden cables on each finger |                                |                                                                | EEG only = 63.59±10.81%                        | EEG only = 63.59±10.81%                        |
|                        |     |        |          | Right hand grasping                                                             |                                   | 5           | Actuation: DC motors with Bowden cables for thumb and index fingers |                                |                                                                | EEG/EOG hybrid = 60.77±9.42%                   | EEG/EOG hybrid = 60.77±9.42%                   |
|                        |     |        |          |                                                                                   |                                   |             | Control: trigger              |                                |                                                                | Mean safety criterion violations during rest: | Mean safety criterion violations during rest: |
|                        |     |        |          |                                                                                   |                                   |             |                                |                                                                | EEG only = 45.91±26.8%                        | EEG only = 45.91±26.8%                        |
|                        |     |        |          |                                                                                   |                                   |             |                                |                                                                | EEG/EOG hybrid = 10.14±0.3%                   | EEG/EOG hybrid = 10.14±0.3%                   |
Zhang et al., 2019
N=6 (2F:4M)
Right-handed
Age range: 23-26y
Implementation of a multimodal system using EEG, EMG and EOG to control a soft-robotic hand
Graz visualisation and auditory instructions, eye movements and physical practice (hand gestures)
Cue: visual (Graz MI), auditory
Feedback: visual and kinaesthetic
EEG with EMG and EOG: 40 channels to analyse ERD/ERS patterns
Device: Soft pneumatic finger
Actuation: pneumatic actuator with soft structures
Control: trigger
Mean classification accuracies:
EOG = 94.23%
EEG = 31.46%
EMG = 36.38%
Multimodal = 93.83±0.02%

UE = Upper Extremity, MI = Motor Imagery, BCI = Brain-Computer Interface, RCT = Randomised Clinical Trial, SAT = Standard Arm Therapy,
EMG = Electromyography, EOG = Electrooculography, ERD/ERS = Event-Related Desynchronisation/Synchronisation, FMMA = Fugl-Meyer Motor Assessment,
ARAT = Action Research Arm Test, GS = Grip Strength, DOF = Degrees-of-Freedom