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Optimizing Non-Invasive Brain-Computer Interfaces for Motor Rehabilitation in Individuals with Spinal Cord Injury

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Abstract

Spinal cord injury (SCI) causes severe motor impairments that significantly reduce patient independence, but cortical networks often remain intact. Non-invasive brain-computer interfaces (BCIs) hold promise for restoring motor control and facilitating rehabilitation after SCI. We conducted a systematic literature review of 100 recent studies on non-invasive BCIs for SCI motor recovery. Our analysis revealed that EEG-based motor-imagery (MI) BCIs paired with functional electrical stimulation (FES) were the predominant approach. These systems often incorporated rich multimodal feedback: many protocols combined visual cues, tactile sensations, and robotic assistance to reinforce the intended movement. We found that providing high density EEG recordings and personalized classifier calibration markedly improved decoding accuracy and clinical outcomes.Key implementation challenges included unstable FES electrode interfaces, user fatigue during extended training, and high system costs. Additionally, most studies tested only small patient cohorts, making it difficult to generalize results; patients with complete neural degeneration cannot benefit from conventional EEG-BCIs, indicating a need for alternative strategies. We highlight advanced adaptive techniques such as deep-learning decoders and transfer learning that have shown promise in recent studies. Overall, aligning neural intent detection with timely stimulation or feedback appears critical for driving neuroplasticity and enhancing motor recovery.

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Introduction

Spinal cord injury (SCI) often results in severe and lasting loss of motor function, greatly reducing patient independence and quality of life. Because cortical and cognitive networks above the injury typically remain intact, non-invasive BCIs have emerged as a promising approach for restoring motor function in SCI patients. In particular, electroencephalography (EEG)-based BCIs using motor imagery (MI) paradigms have shown encouraging results: these systems decode brain activity related to imagined hand or limb movements and translate it into control commands for assistive devices. Functional electrical stimulation (FES) of muscles or robotic exoskeletons are often driven by the decoded signals. In closed-loop studies, pairing EEG-MI with real-time peripheral feedback has facilitated cortical reorganization and produced measurable motor gains in SCI patients.

However, several technical and practical barriers limit widespread adoption of BCIs in SCI rehabilitation. Unstable electrode connections, signal noise, and variability in EEG over time can degrade system reliability. Patients often experience fatigue or discomfort during long training sessions. High-density EEG and sophisticated hardware improve performance butincrease cost and setup complexity. Moreover, existing studies are heterogeneous in design and use various outcome measures, making comparisons difficult. Recent consensus recommendations have emphasized the need for standardized protocols and larger controlled trials to rigorously establish efficacy.

To address these gaps, we conducted a comprehensive review of recent literature on non-invasive BCIs for SCI motor rehabilitation. We focus on identifying BCI design features, signal processing methods, and training protocols that enhance performance and motor recovery. By synthesizing insights across studies, we aim to recommend best practices to optimize BCI design and guide future research in this rapidly advancing field.

Methods

We performed a structured literature review of non-invasive BCIs applied to SCI rehabilitation, following a systematic approach:

- Literature Search: We queried the Web of Science Core Collection with keywords such as “non-invasive brain-computer interface,” “spinal cord injury,” and “motor rehabilitation.” The top 200 articles by relevance were retrieved, and abstracts were screened for relevance to BCI motor therapy. From these, the 100 most-cited publications were selected for detailed analysis.
- Data Extraction: For each selected study, we recorded key details into a spreadsheet. These included the neural recording modality (e.g., scalp EEG, EMG), task paradigm (motor imagery or attempted movement), feedback modalities (visual displays, robotic devices, or FES), and reported outcomes (e.g., classification accuracy or motor improvement).
- Quantitative Analysis: We used software tools (R, Excel) to summarize trends across studies. For example, we quantified publication venues and geographic origins; our analysis confirmed rapid growth in SCI-BCI research worldwide, with major contributions from institutions in the USA and China.
- Qualitative Synthesis: We examined each paper’s conclusions to identify recurring findings. By cross-referencing multiple sources, we identified design elements and protocols consistently linked to positive results. For instance, several studies noted that combining motor imagery training with visual and haptic feedback yields superior rehabilitation outcomes.
- Best Practices: Finally, we synthesized these insights to outline recommendations for optimizing

BCIs. This involved highlighting effective protocols (e.g., session design and calibration), signal processing techniques, and feedback strategies emerging across the literature.

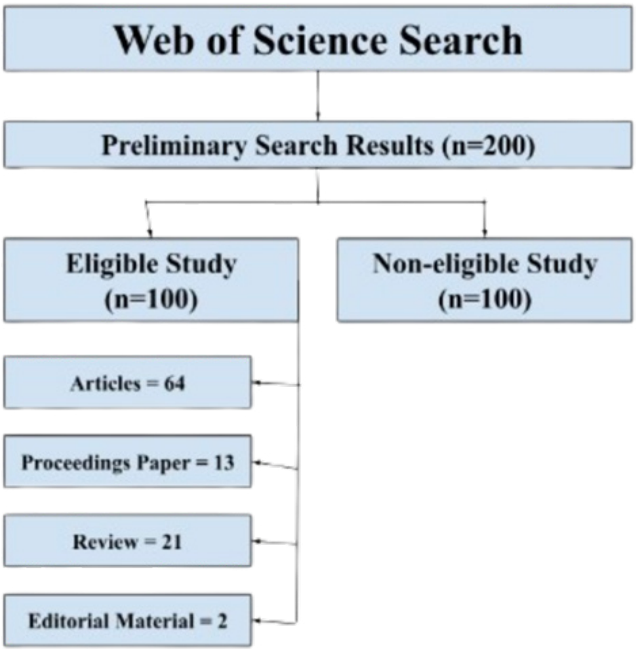

Figure 1

Results

Our analysis of the 100 top-cited publications on non-invasive BCIs for SCI revealed several dominant strategies and themes:

- Dominant Paradigm: The vast majority of reported systems used EEG-based motor imagery (MI) paradigms. In these protocols, patients imagined specific hand or limb movements while real-time EEG decoding targeted sensorimotor rhythm changes (typically decreases in alpha/beta power) to infer intended movement. Functional electrical stimulation (FES) was frequently paired with MI signals: when intent was detected, electrical stimulation activated the corresponding muscles. This closed-loop EEG-MI+FES approach consistently facilitated cortical reorganization and voluntary movement in SCI patients.
- Multimodal Feedback and Personalization: Successful protocols tended to provide rich feedback to the user. Visual feedback (such as a moving cursor or virtual reality cues), haptic feedback (via robotic devices), and proprioceptive input were commonly combined. Notably, systems using high-density EEG and individualized calibration (tuning classifiers to each user) achieved higher decoding accuracy. These personalization strategies, along with combined visual and haptic feedback, significantly improved BCI performance and user engagement.
- Emerging Technologies: Many recent studies have integrated BCIs with novel assistive devices. For example, several groups combined EEG MI with transcutaneous spinal cord stimulation, showing synergistic effects on learning. Robotic exoskeletons (e.g., gait trainers like the Lokomat) and soft robotic gloves driven by advanced decoders have also been proposed for rehabilitation, reflecting a trend toward hybrid BCI-robotic systems.
- Implementation Challenges: Common obstacles were identified across studies. FES electrode placement often proved unstable, reducing stimulation reliability. Users commonly reported fatigue or discomfort during prolonged EEG sessions. While high-density EEG systems improve accuracy, they increase cost and preparation time. Crucially, most studies involved only small numbers of patients (typically under 20) with short intervention periods, and they used heterogeneous outcome measures (different motor scales and endpoints), making it difficult to compare results across studies.

- Key Facilitators: Across the literature, certain factors consistently correlated with better outcomes. Intensive user training with rich feedback led to greater motor improvements. BCIs that adapted over time (for example by retraining classifiers or using transfer learning across sessions) showed improved stability. Although few studies explicitly used advanced machine learning, those that did reported higher accuracy. In summary, personalized calibration and closed-loop multimodal feedback emerged as recurrent facilitators of high BCI performance.

In summary, these results indicate that EEG-MI paradigms with robust feedback are the most effective strategy for SCI rehabilitation BCIs. Optimizing system parameters (such as electrode density and classifier tuning) and incorporating multisensory feedback consistently improves motor outcomes.

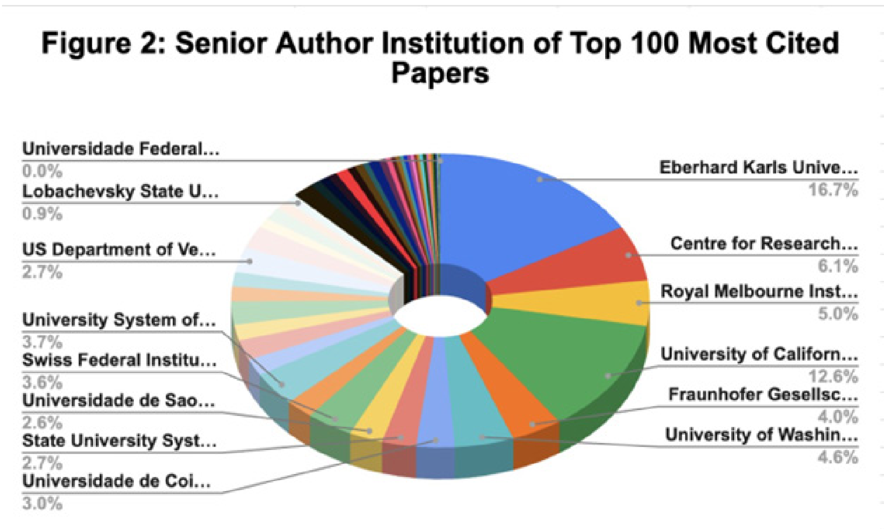

Figure 2

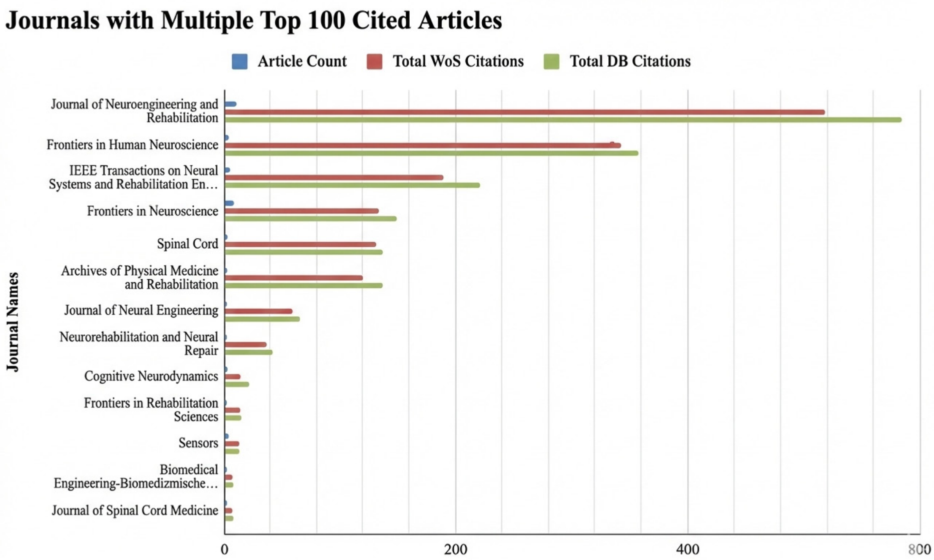

Figure 3

Discussion

Our review confirms and extends prior findings in SCI rehabilitation. We found that non-invasive BCIs using EEG-MI paired with FES or robotic feedback can yield tangible rehabilitation benefits. The timing of feedback was critical: systems that synchronized stimulation or device actuation with the user's motor intent appeared to maximize neuroplastic gains. This aligns with clinical studies demonstrating significant motor improvements from closed-loop BCI protocols.

Personalization was another key theme. Studies that calibrated signal processing to each patient (adjusting frequency bands or classifier parameters) reported much higher accuracy. Modern adaptive algorithms, such as those based on deep learning or transformer networks, can facilitate this personalization. For example, transformer-based decoders have shown promise in capturing complex EEG patterns; incorporating such advanced methods may mitigate EEG variability and enhance performance across sessions.

Despite these advances, persistent challenges remain. Long-duration EEG training can degrade signal quality and increase subject fatigue. High-density EEG and multi-channel FES systems, while effective, are expensive and cumbersome. We also note an unmet need for severely paralyzed patients: conventional EEG-BCIs cannot serve individuals with complete motor degeneration, indicating that alternative assistive solutions (such as brain-controlled prosthetic devices) are needed for this group.

An overarching limitation is the scale of the current evidence. Many positive results come from small pilot studies rather than large clinical trials. We echo recent consensus calls for standardized protocols and multi center trials in SCI rehabilitation. To facilitate this, we recommend the following best practices:

- Standardization: Adopt common outcome metrics and uniform intervention protocols. Large multi-center trials using standardized measures will enable robust evaluation of BCI efficacy.
- Affordable Hardware: Develop cost-effective dry-electrode EEG caps to reduce setup time and improve signal stability. Cheaper, easier-to-use hardware will make BCIs more practical in clinical settings.
- Advanced Signal Processing: Incorporate real-time artifact rejection and adaptive machine learning algorithms to maintain performance over long-term use and across sessions.
- Enhanced Feedback: Integrate richer sensory feedback (e.g., immersive virtual reality, haptic force feedback) to sustain user engagement and amplify neuroplasticity beyond traditional visual cues.
- Interdisciplinary Collaboration: Promote collaboration among engineers, neuroscientists, and clinicians to tailor BCI systems to patient needs and ensure safety and usability in rehabilitation.
- By addressing these areas, future BCIs can better translate laboratory advances into clinical impact [1-16].

Conclusion

Non-invasive BCIs have demonstrated the capacity to enhance motor rehabilitation in individuals with SCI, especially when EEG-based MI training is combined with FES and personalized protocols. These systems can induce cortical reorganization and promote partial recovery of voluntary movement. However, broader clinical impact will require overcoming practical challenges: reducing hardware costs, improving electrode stability, and standardizing intervention protocols. Next-generation BCIs should leverage adaptive algorithms (e.g., deep learning, transfer learning) to improve decoding accuracy and allow cross-session generalization, and they should incorporate alternative assistive solutions (such as brain-controlled devices) for patients with complete paralysis who cannot benefit from EEG-based control.In summary, while challenges remain, advances in BCI technology, neuroscience, and rehabilitation practice position non-invasive BCIs as a promising pathway to restoring lost motor function in SCI patients. Future large-scale, rigorous trials with standardized outcome measures will be needed to translate these research advances into standard clinical therapies.

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