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Bridging Minds and Machines: The Recent Advances of Brain-Computer Interfaces in Neurological and Neurosurgical Applications

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Key words

- Brain-computer interface
- Functional electrical stimulation
- Neurology
- Neurosurgery

Abbreviations and Acronyms

AD: Alzheimer disease
AI: Artificial intelligence
ALS: Amyotrophic lateral sclerosis
AVM: Arteriovenous malformation
BCI: Brain-computer interface
CNS: Central nervous system
CVD: Cerebrovascular diseases
DBS: Deep brain stimulator
ECoG: Electrocorticography
EEG: Electroencephalography
FES: Functional electrical stimulation
ITR: Information transfer rate
MDD: Major depressive disorder
P300: P300 evoked potentials
PD: Parkinson disease
SCD: Spinal cord disease
SCI: Spinal cord injury
SSVEP: Steady-state visual evoked potentials
VR: Virtual reality

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Brain-computer interfaces (BCIs), a remarkable technological advancement in neurology and neurosurgery, mark a significant leap since the inception of electroencephalography in 1924. These interfaces effectively convert central nervous system signals into commands for external devices, offering revolutionary benefits to patients with severe communication and motor impairments due to a myriad of neurological conditions like stroke, spinal cord injuries, and neurodegenerative disorders. BCIs enable these individuals to communicate and interact with their environment, using their brain signals to operate interfaces for communication and environmental control. This technology is especially crucial for those completely locked in, providing a communication lifeline where other methods fall short. The advantages of BCIs are profound, offering autonomy and an improved quality of life for patients with severe disabilities. They allow for direct interaction with various devices and prostheses, bypassing damaged or nonfunctional neural pathways. However, challenges persist, including the complexity of accurately interpreting brain signals, the need for individual calibration, and ensuring reliable, long-term use. Additionally, ethical considerations arise regarding autonomy, consent, and the potential for dependence on technology. Despite these challenges, BCIs represent a transformative development in neurotechnology, promising enhanced patient outcomes and a deeper understanding of brain-machine interfaces.

INTRODUCTION

Significant advancements in neurology and neurosurgery have spurred technological innovation, notably with Hanns Berger's invention of electroencephalography (EEG) in 1924, revolutionizing brain activity recording.[1] This led to further developments in neurotechnology, including neural prosthetics like deep brain stimulators (DBSs), which have been instrumental in treating conditions such as stroke and epilepsy.[2] Additionally, recent integration of robotics and virtual reality (VR) has enhanced the management of neurological conditions, improving patient outcomes.[3] Brain-computer interfaces (BCIs) have emerged as a pioneering technology, aiming to create an efficient brain-machine interface by converting central nervous system (CNS) signals into commands for external devices.[4] BCIs are extensively researched, particularly for clinical applications among patients with communication and motor function impairments due to conditions like amyotrophic lateral sclerosis (ALS), stroke, and spinal cord injury (SCI).[5] These devices harness neural signals to operate alphanumeric grids, cursors, and web browsing tools, facilitating communication for individuals lacking functioning peripheral nervous systems and muscular activity.[6]

The BCI comprises four main components: a signal acquisition unit, signal processing unit, controlling unit, and application. Probes in BCI are categorized into: microelectrodes, optoprobes, and magnetrodes.[7] BCIs are categorized based on invasiveness and signal processing synchronization into invasive, partially invasive, and noninvasive types. Invasive BCIs involve direct interaction with intracortical electrodes, offering high accuracy but posing significant risks due to scar tissue formation.[8] Partially invasive BCIs position electrodes under the skull, exemplified by electrocorticography (ECoG).[9] Noninvasive BCIs, like EEG and magnetoencephalography, monitor brain activity externally without surgery.[10] BCIs are further categorized as synchronous or asynchronous, with synchronous versions initiating interactions after a cue, while asynchronous BCIs rely on user-initiated tasks.[9] Lastly, BCIs can be dependent, requiring motor control, or independent, useful for users with motor deficits.[11]

Augmentative and alternative communication methods, such as combining eye-trackers and speech-generating devices, have proven beneficial for patients with functional motor channels, aiding their communication needs.[12] However, these strategies are ineffective for individuals with locked-in syndrome or complete locked-in syndrome who have lost all motor channels. In such cases, BCIs offer promising solutions to address communication difficulties.[13] BCIs provide an avenue for individuals without limb function to communicate and engage by controlling household devices and neural prostheses for mobility.[14] This direct connection between the brain and external devices signifies a significant advancement in neurotechnology.

Similar to any other technology, BCIs have drawbacks and obstacles. Challenges related to usability involve the time-consuming process of user training and the limited rate of information transfer.[15] User training can be a lengthy task, and certain types of BCIs, such as imagery-based BCIs, have a lower information transfer rate (ITR) compared to other types.[15] Technical challenges encompass issues like nonlinearity, nonstationarity, limited training data sets, and the burden of high dimensionality.[15]

The objective of this review is to highlight recent progress in the application of BCIs within the realms of neurosurgery and neurology.

METHODOLOGY

This review comprehensively assesses the application of BCI in neurosurgery and neurology. The inclusion criteria for this review encompassed only full-text articles written in English.

The inclusion criteria for this review consisted of full-text articles written in English, spanning from 2000 to 2023. This time period was chosen to allow for a thorough evaluation of established practices within the field as well as to capture any significant advancements that occurred over a substantial period of time. Several databases were employed to ensure an exhaustive literature search, including PubMed, EMBASE, Google Scholar, the Cochrane Library, and Scopus. Key terms such as "brain-computer interface" and "neuro technology" were used in all searches, accompanied by additional terms comprising "Neurodegenerative Disorders", "Cerebrovascular Disorders", "neuro-oncology", "Brain tumours", "Spinal cord tumours", "Spinal cord diseases", "strokes", "epilepsy", and "seizures".

Additional sources were identified to augment the search strategy through a manual search of references cited in recent reviews focused on specific diseases. Rigorous exclusion criteria were adopted, involving the exclusion of standalone abstracts, case reports, posters, and unpublished or nonpeer-reviewed studies. By instituting these criteria, the review sought to ensure the inclusion of high-quality and reliable evidence.

As for the scope of the review, no predetermined limit was set on the number of studies to be included, a strategy designed to gather comprehensive knowledge on the subject matter. The review included a range of study designs, including descriptive studies, animal-model studies, cohort studies, and observational studies. Moreover, it encompassed investigations conducted in preclinical and clinical settings, offering a broad perspective on the use of BCI in neurology and neurosurgery. A summary of the methodology employed is presented in Table 1.

Table 1. Summary of Methodology for This Review

Methodology Steps	Description
Literature search	PubMed, EMBASE, Google Scholar, the Cochrane Library, and Scopus
Inclusion criteria	- Full-text articles published in English - Focus on applications in neurology and neurosurgery - Adult and pediatric populations
Exclusion criteria	- Stand-alone abstracts - Case reports - Posters - Unpublished or non-peer-reviewed studies
Search terms	Keywords such as "brain computer interface" and "Neuro technology" coupled with indicators like "Neurodegenerative Disorders", "Cerebrovascular Disorders", "Neuro-oncology", "Brain tumours", "Spinal cord tumours", "Spinal cord diseases", "strokes", "epilepsy", and "seizures"
Additional search	- Manual examination of references cited in recent disease-specific reviews - No predetermined limit on the number of studies - Encompassing diverse study designs: ● Descriptive studies ● Animal-model studies ● Cohort studies ● Observational studies - Including investigations in both preclinical and clinical settings

RECENT ADVANCEMENTS AND APPLICATIONS OF BCI IN NEUROLOGICAL AND NEUROSURGICAL DISEASES

Cerebrovascular Diseases

BCIs have shown promise in addressing cerebrovascular diseases (CVDs) like stroke, cerebral aneurysms, arteriovenous malformations (AVMs), and cerebral ischemia by recording brain activity. However, the development of BCIs in these areas is still in its early stages, with a primary focus on stroke as the main application of BCIs in CVDs.[16]

Stroke. Stroke is a leading cause of disability worldwide, characterized by a range of impairments including motor, cognitive, communicative, and emotional challenges.[17,18] Advanced technologies like BCIs, alongside conventional therapies, have significantly improved poststroke rehabilitation. BCIs, in particular, have shown efficacy in restoring motor functions and enhancing cognitive and emotional well-being in stroke patients.[3,19-21] Their role extends beyond motor rehabilitation, encompassing diagnosis, preoperative planning, intraoperative monitoring, and enhancing safety in neurosurgical procedures.[15,22,23] The integration of BCI with end-effectors like functional electrical stimulation (FES), VR, transcranial direct current stimulation, and robotic devices has facilitated significant improvements in motor function, communication, and cognitive abilities in stroke survivors.[19,21,24-26]

Stroke rehabilitation through BCI encompasses two primary approaches: assistive and rehabilitative. Assistive BCI provides alternative communication and control methods for permanent disabilities, while rehabilitative BCI aims at restoring impaired brain functions by leveraging neuroplasticity.[5,27] This involves techniques like neurofeedback training, operant conditioning, and Hebbian learning to stimulate brain activity and re-establish sensorimotor loops.[28-30] For example, novel interventions like BCI-controlled pedaling training systems not only boosted motor function but also addressed cognitive aspects in patients with ischemic stroke.[31]

Furthermore, BCIs also contribute to sensory and communication rehabilitation in stroke patients. Sensory rehabilitation through BCI remains underexplored but holds potential for improving motor and tactile impairments.[32] Through the integration of BCI and FES technologies, a novel artificial neural rehabilitation system demonstrated significantly greater improvements in motor function, gait velocity, cadence, Fugl Meyer Assessment of the Upper Extremity, and Kendall manual muscle testing scores compared to the control group receiving neuromuscular electrical stimulation.[33,34] In communication rehabilitation, BCIs have been effective in addressing poststroke aphasia, utilizing EEG signals for language communication, and improving speech deficits.[35,36] Overall, BCIs represent a promising and evolving area in stroke recovery, offering novel pathways for enhancing the quality of life for stroke survivors.

Other CVDs. This section explores the burgeoning field of utilizing BCI technology in the management of other CVDs, such as cerebral aneurysms and AVMs. Computational fluid-structure interaction models have played a pivotal role in advancing our understanding of the pathophysiology of CVDs.[37] Surgical planning for AVM resection, facilitated by a VR system—a type of BCI—has demonstrated its efficacy in conducting detailed analyses of 3-dimensional multimodality imaging data.[38] Such an approach enhances surgical strategy development, intraoperative spatial orientation, and surgeon confidence.[38]

In the context of cerebral aneurysms, BCI has proven instrumental in both constructing predictive models and improving surgical performance. Computational fluid dynamics simulations and shape analyses have been employed to quantitatively characterize the shape and hemodynamics of cerebral aneurysms.[39] A rupture probability model, derived through BCI and statistical analyses, underscores the population-specific differences in determining the association between hemodynamics, shape, and rupture risk in intracranial aneurysms.[39] These findings contribute to the development of personalized medicine, enabling tailored treatment plans based on individual patient characteristics. Virtual stenting workflows, involving the modeling of stent and flow diverter deployment in patient-specific aneurysms, have shown promise in rapidly simulating clinical deployment of these interventions.[40] This paves the way for potential future clinical implementations, thereby advancing the field of neurosurgical procedures for intracranial aneurysms.

The integration of a VR clipping simulator, designed with interactive brain-deforming capabilities and a focus on supporting tissues, has proven instrumental in advancing the surgical simulation of cerebral aneurysm clipping.[41] This innovative approach, characterized by modifiable cerebral tissue complex deformation through multi-tissue integrated interactive deformation, incorporates nonmedical image-derived virtual arachnoid/trabeculae, enhancing the simulator's capacity to simulate dynamic interactions within the aneurysm environment.[41] Additionally, the creation of a multilayer fusion image from 3-dimensional computed tomographic angiography (CTA) data provides comprehensive anatomical information about the aneurysm and its surroundings, significantly improving diagnostic imaging capabilities and offering valuable image-guided support for neurosurgical procedures in intracranial aneurysm cases.[42] This integrated approach represents a notable leap forward in refining the surgical training experience for cerebral aneurysm interventions.

The incorporation of BCI in the management of CVDs, particularly cerebral aneurysms and AVMs, showcases its potential to revolutionize surgical planning, enhance diagnostic imaging, and facilitate personalized treatment strategies. This comprehensive review amalgamates evidence from recent studies, shedding light on the evolving landscape of BCI applications in neurosurgery. Figure 1 depicts the integration of BCI technology in cerebrovascular health care, showcasing its capability in both rehabilitation following stroke and in providing insights into the mechanisms of cerebral aneurysms and AVMs.

Neurodegenerative Diseases

BCIs are revolutionizing the management of various neurodegenerative diseases such as dementia, Alzheimer disease (AD), Parkinson disease (PD), and ALS. In dementia care, BCIs have shown remarkable utility. Character-input-type BCIs, for instance, have effectively differentiated between AD, Lewy body dementia, and mild cognitive impairment in elderly patients by analyzing character-gazing

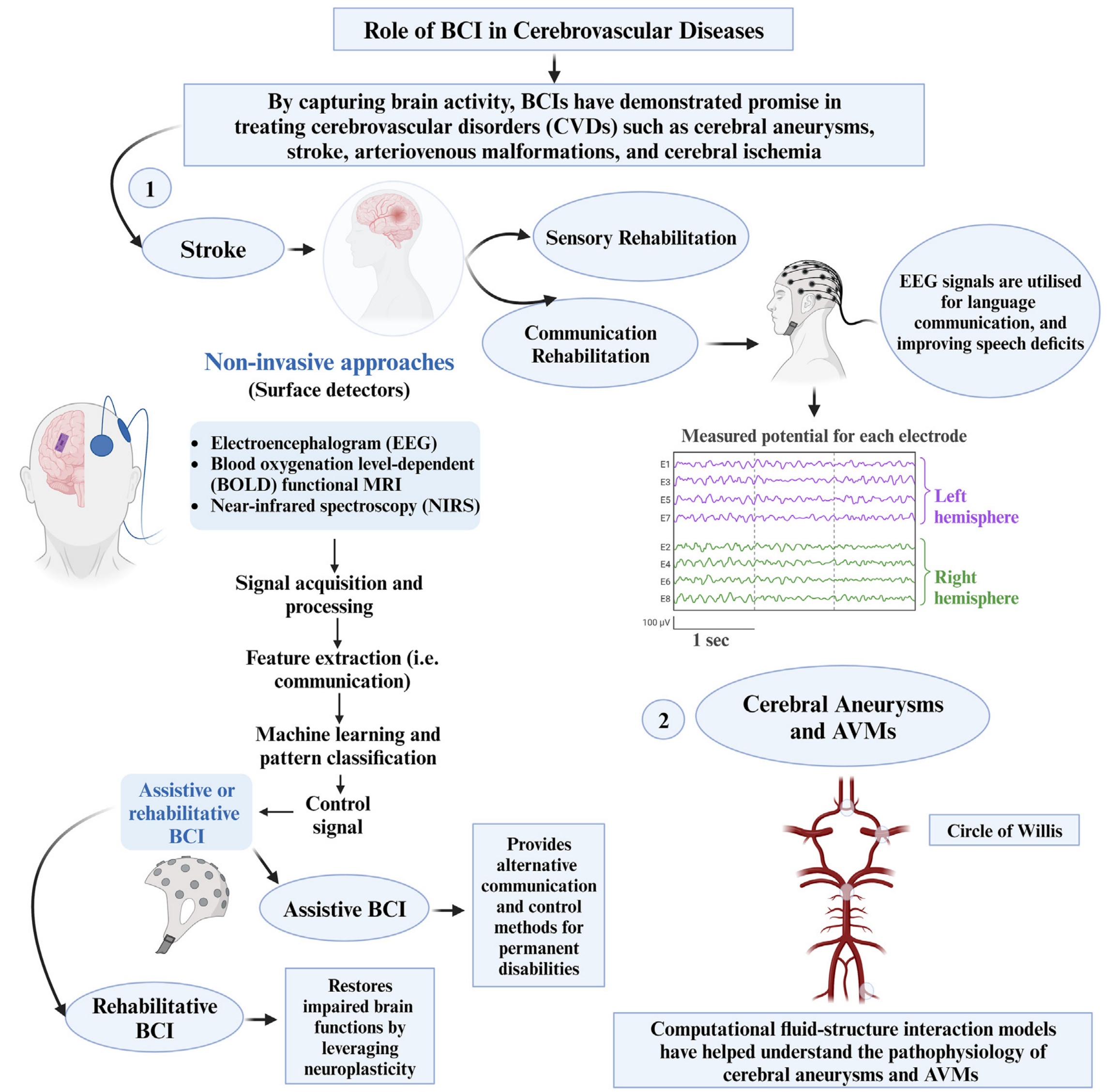

Figure 1. A graphical representation of the numerous applications of brain-computer interface in cerebrovascular disease management. Original figure prepared using Biorender.com Abbreviations: BCI, brain-computer interface; CVD, cerebrovascular disorder; EEG, electroencephalogram; BOLD-MRI, blood oxygenation level-dependent magnetic resonance imaging; NIRS, near-infrared spectroscopy; AVM, arteriovenous malformations.

patterns, achieving a moderate success rate in classification.[43] In addition, BCI-based cognitive training has significantly enhanced cognitive functions in dementia patients over the past six weeks, outperforming traditional interventions like music and physical exercises. Furthermore, passive BCIs using EEGs have been instrumental in diagnosing early-onset dementia.[44] For AD, nBCIs employing EEGs have demonstrated high accuracy (86.47%) in distinguishing AD from mild cognitive impairment and healthy states, aiding in early detection.[45] Moreover, magnetic resonance imaging (MRI) coupled with a support vector machine classifier, focusing on key brain regions such as the insula, amygdala, and anterior cingulate cortex, has shown potential in differentiating mental states elicited by word pairs, a promising approach for enhancing communication and aiding in the rehabilitation and diagnosis of AD patients.[46]

In PD management, BCIs are showing transformative effects. The BCI Touch application allows elderly individuals with psychomotor impairments to interact with mobile devices using brainwave patterns, thus enhancing their technological autonomy.[47] In clinical settings, BCI-controlled adaptive deep brain stimulation has proved more effective and efficient than traditional continuous stimulation.[48] Additionally, advancements in motor-imagery-based BCIs, like the introduction of the multi-session filter-bank common spatial patterns method, have significantly improved calibration accuracy, demonstrating the effectiveness of advanced BCI technologies in enhancing neurorehabilitation for PD patients.[49] For example, BCIs are also critical in managing ALS. P300 evoked potentials (P300)-based BCIs align well with standard cognitive assessments and effectively distinguish ALS patients from healthy controls based on cognitive task execution times.[50] Fully implanted ECoG-based BCIs have shown stable performance over extended periods, offering effective communication solutions for late-stage ALS patients.[51] Additionally, research indicates that while most ALS patients can successfully use visual P300-based BCIs, in the advanced stages of ALS, where muscular control is severely impaired or lost entirely, traditional BCIs reliant on visual cues become ineffective.[52,53] Here, auditory-based BCIs are a viable alternative.[52] The significance lies in the BCI's ability to offer binary (yes/no) communication independent of visual cues, making it particularly suitable for patients with complete motor loss and limited attention spans. Results demonstrated impressive performance, with an average ITR of up to 2.46 bits per minute and accuracies reaching 78.5%.[53]

Additionally, individuals with tetraplegia secondary to ALS utilized a simple communication BCI based on intracortical local field potentials for extended periods up to 138 days, without the need for recalibration or significant loss of performance.[54] With typing rates of up to 6.88 correct characters per minute, these individuals were able to effectively communicate through typing messages and writing emails, thereby enhancing their independence and quality of life.[54]

Recent research also underscores additional devices and features that could potentially augment the management of ALS patients dependent on BCIs. Studies on the frontal steady-state visual evoked potential (SSVEP) in BCIs indicate varying levels of control efficiency among young subjects, elders, and ALS patients, with the frontal SSVEP emerging as a feasible control signal for SSVEP-based BCIs.[55] Additionally, the significance of attentional processes in ALS patients has been observed through the revelation that temporal filtering capacity strongly predicts performance in P300-based BCI tasks.[56] Collectively, these studies underscore the potential of BCIs to provide tailored and effective management strategies for ALS, adapting to individual cognitive and neurological profiles. Figure 2 provides an overview of the application of BCI technology in the context of neurodegenerative diseases.

Neuro-Oncological Diseases

The integration of BCI technologies, particularly scalp EEG, is revolutionizing the diagnosis and management of brain tumors. The development of automated systems using scalp EEG, such as modified wavelet-independent component analysis combined with neural networks, is proving effective in detecting brain tumors, leveraging the advantages of cost-effectiveness and noninvasiveness.[57] These systems utilize first-, second-, and third-order statistics of EEG signals for tumor detection and are complemented by techniques employing multiwavelet transforms and neural networks to classify EEG signals for primary brain tumor detection, emphasizing the measurement of signal irregularities through approximate entropy.[57,58] The convergence of these advanced techniques represents a significant stride in medical technology, offering more reliable and efficient diagnostic tools for brain tumor identification and monitoring.

BCIs and neurofeedback technologies are increasingly recognized for their therapeutic potential in addressing complications associated with brain tumor treatments. The use of connectome-based transcranial magnetic stimulation in glioma patients with postoperative deficits has demonstrated safety and efficacy in promoting functional recovery, with a majority of patients experiencing significant clinical improvements without serious complications.[59] Additionally, a study on chemotherapy-induced peripheral neuropathy in cancer survivors revealed that neurofeedback treatments led to long-term reductions in pain severity and improvements in quality of life, physical functioning, and fatigue.[60] These findings collectively underscore the potential of BCIs and neurofeedback to enhance rehabilitation and quality of life for patients suffering from brain tumors and the side effects of cancer treatments, indicating a promising avenue for future clinical trials and therapeutic strategies. Figure 3 highlights the pivotal role of BCI technology in improving diagnostic processes for brain tumors and in providing therapeutic interventions to address the complications associated with brain tumor treatments, such as postoperative deficits and chemotherapy-induced neuropathy.

Epilepsy and Seizure Disorders

Epilepsy stands as a significant global health challenge.[61] Despite significant strides, there is a pressing need for innovative approaches to understand, monitor, and treat epilepsy. Conventional methods, while valuable, often need to provide real-time insights into the dynamic nature of seizures and the individualized characteristics of the disorder.[62] One notable challenge lies in the imprecise nature of existing monitoring techniques.[63] Traditional methods often rely on intermittent assessments, such as EEG recordings during clinic visits, which do not capture the full spectrum of a patient's seizure activity.[64] This sporadic monitoring often results in an incomplete understanding of seizures' frequency, duration, and patterns, limiting the ability to tailor interventions to the individual's needs.[64] This is where BCIs emerge as a promising frontier in epilepsy management.

Recent breakthroughs in neuroscience and technology have propelled BCIs to the forefront of epilepsy management. Integrating BCIs into wearable devices has enabled continuous ambulatory monitoring, empowering individuals to go about their daily lives while electrical activities for seizures are continuously monitored.[65] Integrating BCIs into seizure monitoring represents a groundbreaking approach to understanding the dynamics of epileptic events. This enhances the quality of the data collected and provides a more holistic view of the individual's seizure patterns. Moreover, cutting-edge BCIs have leveraged real-time EEG analysis to detect brain electrical activities for epilepsy detection.[66] Recently, BCIs have also been proven effective in drug-resistant epilepsy. This is done through responsive neural stimulation (detection)

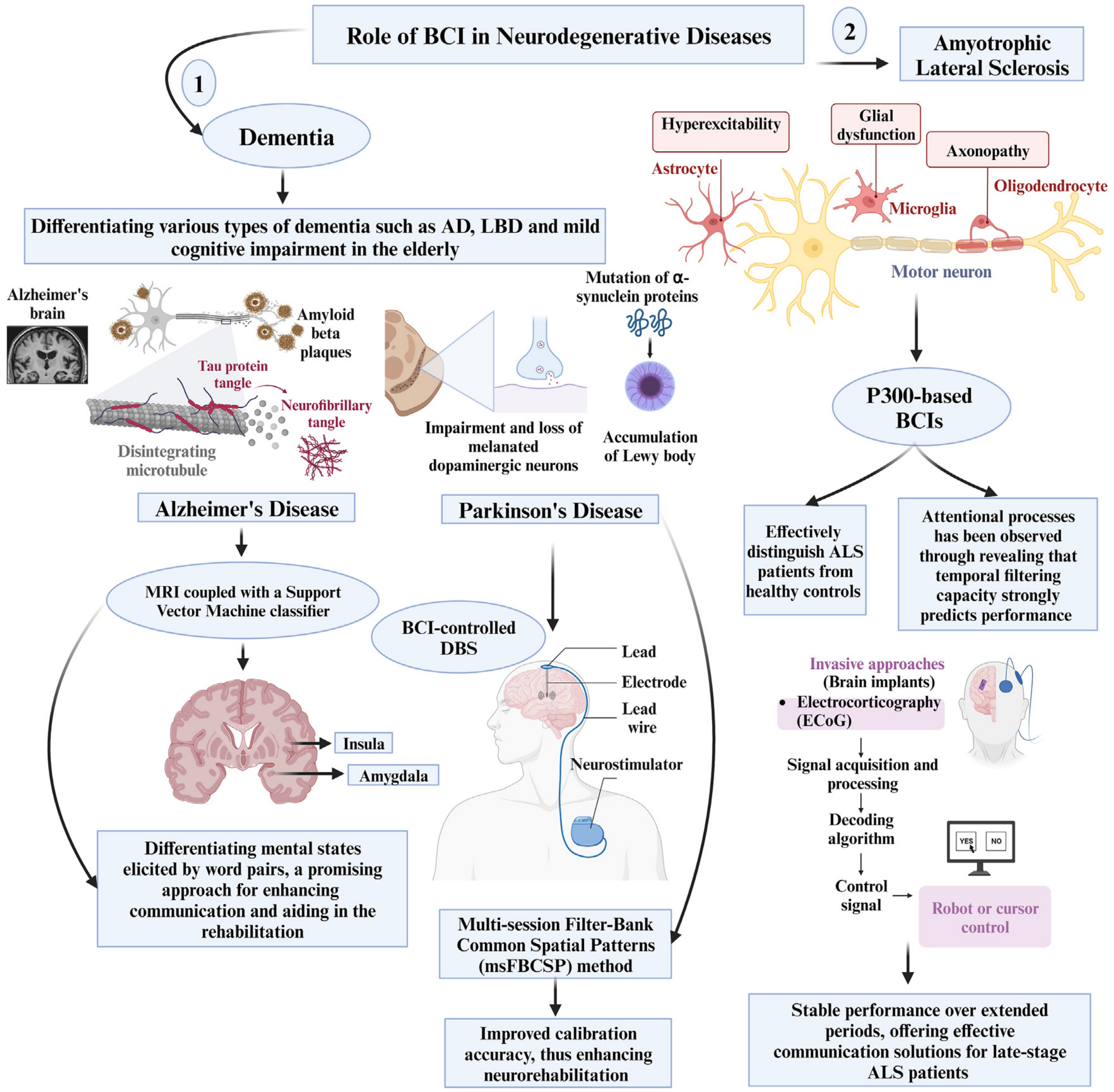

Figure 2. Illustration representing applications of brain-computer interface in neurodegenerative diseases. Original figure prepared using Biorender.com Abbreviations: BCI, brain-computer interface; AD, Alzheimer disease; LBD, Lewy body dementia; DBS, deep brain stimulation; msFBCSP, multi-session filter bank common spatial patterns; ALS, amyotrophic lateral sclerosis; ECoG, electrocorticography.

as well as electrical stimulation for modulation.[67]

Furthermore, BCIs equipped with advanced machine-learning algorithms have shown promise in predicting seizures with high accuracy.[68] A study by Anter et al. (2022) employed machine learning algorithms to classify seizure states from EEG.[69] These algorithms learn individualized patterns of brain activity that precede seizures. However, seizure predictions currently remain unsolved within absence seizures due to the sudden nature of onset. Current research is underway to create algorithms that can predict absence seizures with some nearing 97.20% accuracy.[70,71] All in all, utilizing BCI technology in epilepsy, as shown in **Figure 4**, enables the real-time capture and analysis of EEG data, facilitating advanced seizure prediction through machine learning algorithms.

Spinal Cord Diseases

Spinal cord diseases (SCDs) encompass a wide array of pathologies, predominantly caused by external factors such as trauma, tumors, spinal stenosis, herniated discs, and abscesses. In fewer instances, they are due to intrinsic causes like hemorrhage, infarction,

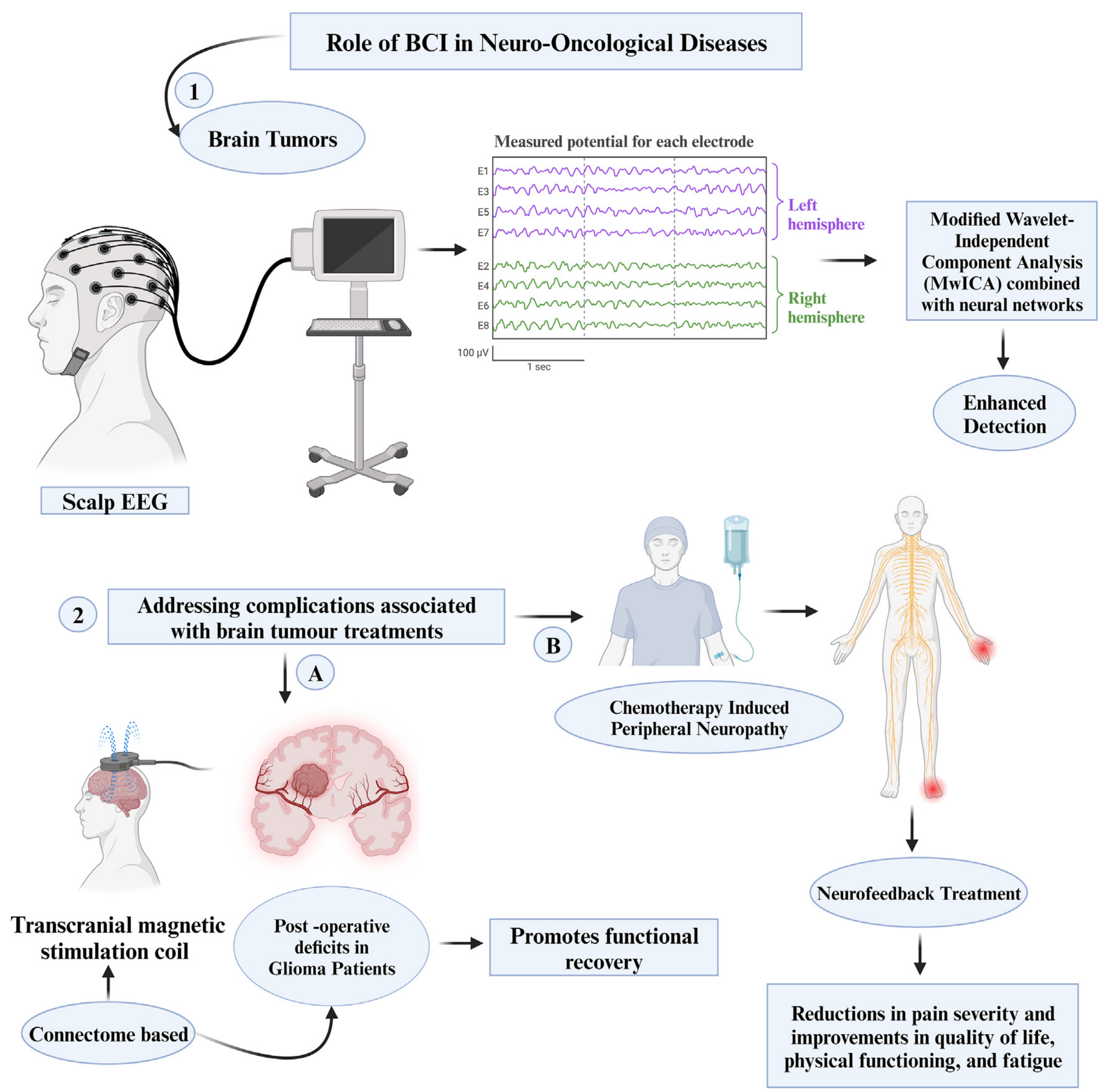

Figure 3. Schematic diagram highlighting the role of brain-computer interface in neuro-oncological care, from electroencephalography (EEG)-based tumor detection to neurofeedback therapies for treatment-related neuropathy and functional recovery postsurgery. Original figure prepared using biorender.com Abbreviations: BCI, brain-computer interface; MwICA, modified-wavelength independent component analysis.

vitamin B12 deficiency, and syphilis.[72] Traditional treatments primarily focus on reducing inflammation using steroids and immune modulators. However, recent advancements have shifted attention towards BCI-based therapies, particularly in their role in controlling prostheses.

SCDs disrupt the spinal cord's ability to communicate signals for limb movement. A brain-spine interface aims to rectify this by directly connecting cortical signals to the spinal cord.[73] The BCI, an innovative approach in SCD treatment, decodes brain signals indicating movement intentions and translates them into motor stimulation.[74] These interfaces are quickly calibrated and provide patients with naturalistic control over their movements. Beyond immediate functional benefits, BCIs also contribute to neurorehabilitation, offering sustained improvements postdiscontinuation.[75]

For SCIs above the C5 level, where surgical options are available, BCIs have emerged as a vital treatment modality. Traditional motor-driven orthoses are often impractical due to their complexity and cost, primarily serving as training devices.[76] BCIs, in contrast, enable upper extremity function restoration through neuroprostheses that operate on FES. This involves short current pulses that activate nerves to induce muscle contraction. The most effective approach involves noninvasive neuroprostheses with multiple surface electrodes, although their efficacy is

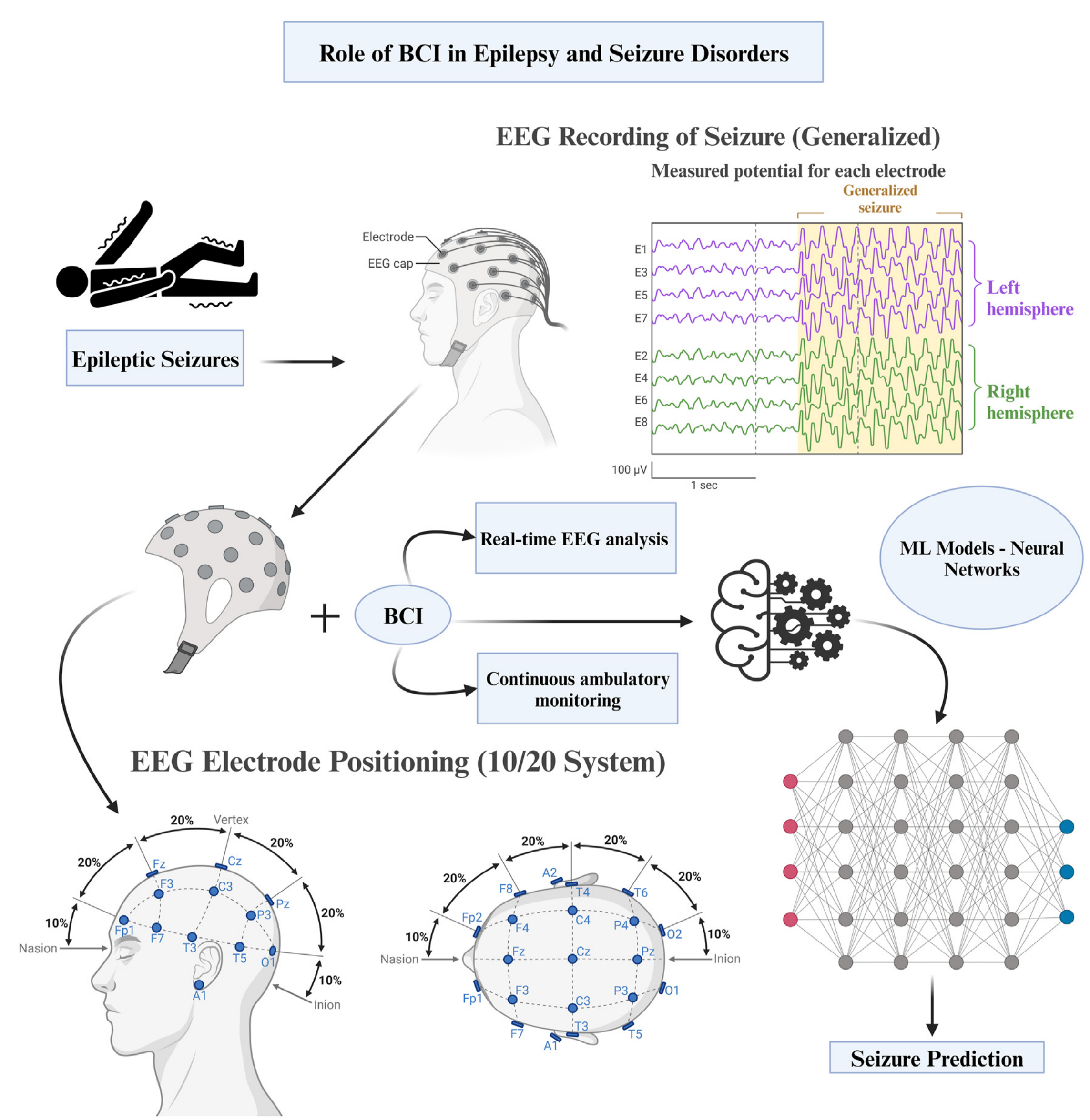

Figure 4. Overview of brain-computer interface utilization for epilepsy and seizure monitoring. Original figure prepared using Biorender.com Abbreviations: BCI, brain-computer interface; EEG, electroencephalogram; ML, machine learning.

primarily in hand grasping, as supporting elbow function is hindered by rapid muscular fatigue.[77] For example, in the context of traumatic cervical SCI, where sensorimotor abilities are severely impacted, BCIs offer promising solutions to enhance hand function recovery.[78] The "DiSCIoser" study focuses on utilizing BCI-supported motor imagery training to engage the sensorimotor system, fostering neuroplasticity during the subacute phase of SCI recovery.[78]

The combination of BCI with FES for hand therapy among individuals with SCI revealed promising effectiveness, with BCI accuracy ranging from 70% to 90%, median donning times decreasing from 40.5 to 27 minutes during training times, and further to 14 minutes during self-managed sessions.[79] Furthermore, BrainGate feasibility study demonstrated a favorable safety profile of the utilization of BCIs in SCI.[80] Particularly, no events necessitated device explanation or resulted in death or permanently increased disability, suggesting a promising risk-benefit ratio for BCI use in individuals with SCI.[80]

Moreover, BCIs extend their utility to diagnosing and predicting abnormal CNS structures like tumors, offering a cost-effective alternative to computed tomography scans and magnetic resonance imaging through EEG.[15] Looking ahead, ECoG devices show promise in aiding rehabilitation post-tumor resection by enhancing brain-spinal cord plasticity and

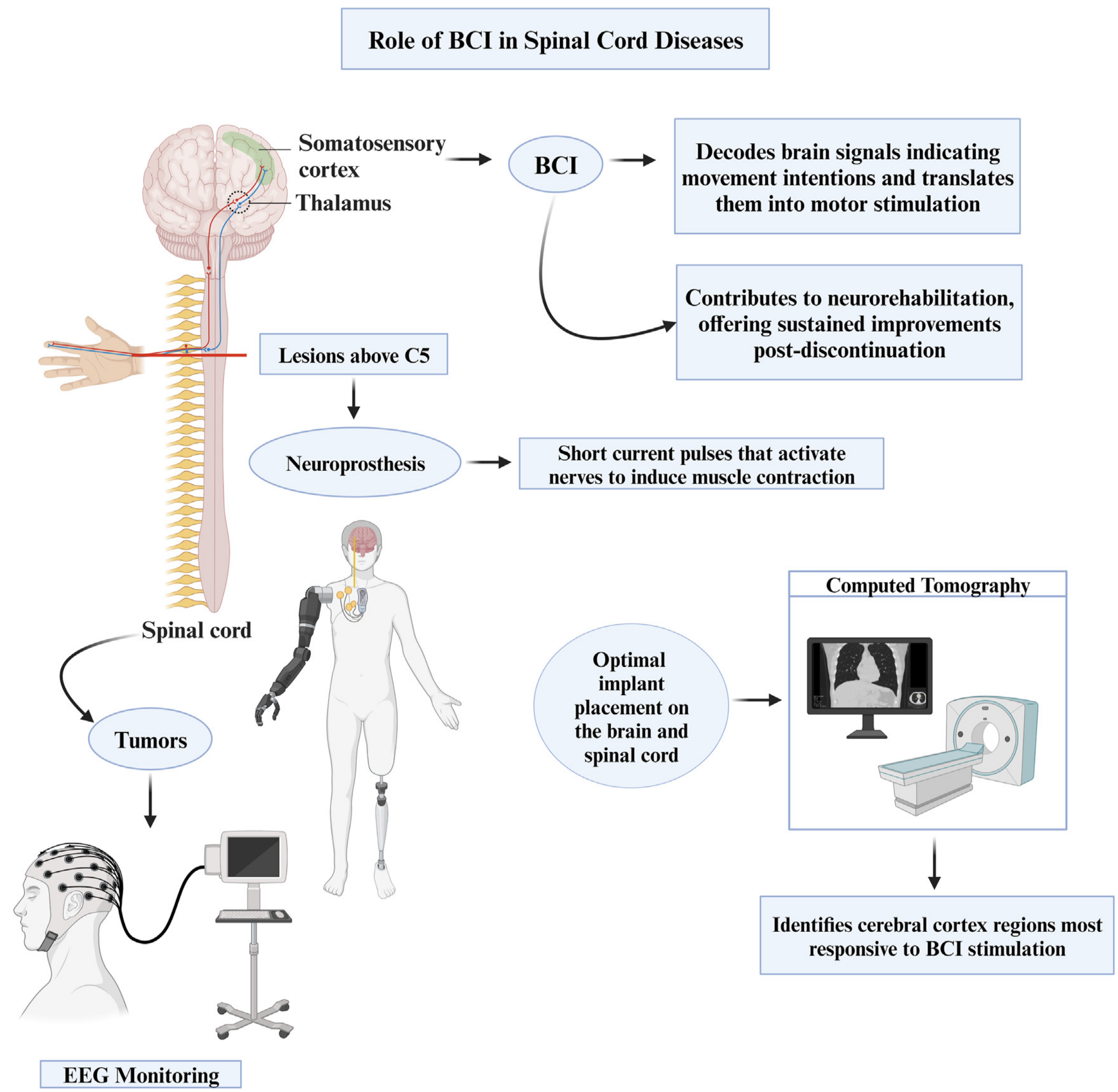

Figure 5. Schematic representation of the role of brain-computer interfaces (BCIs) in the management of spinal cord diseases. Original figure prepared using biorender.com Abbreviations: BCI, brain-computer interface.

aiding neural regeneration, rooted in Hebb's postulate of neuronal connectivity.[81]

Implementing BCIs requires precise preoperative planning to ensure optimal implant placement on the brain and spinal cord. This involves using computerized tomography to identify cerebral cortex regions most responsive to BCI stimulation, ensuring effective detection of limb movement intentions.[75] Figure 5 illustrates the pathway through which BCI technology deciphers neural signals for the activation of neuroprostheses, offering a promising avenue for the restoration of motor functions in individuals afflicted with SCDs.

APPLICATIONS OF BCI FOR NEUROEDUCATIONAL PURPOSES

BCIs possess transformative potential within neuroeducation, benefiting diverse cohorts, including patients with neurological impairments, medical students, and practicing physicians. Particularly for patients grappling with severe motor or communication disabilities, BCIs represent a groundbreaking advancement. They empower individuals to control computer screens, neuroprostheses, and internet access, thereby facilitating education, communication, and environmental control.[82] This technology notably impacts individuals with conditions such as SCIs, stroke, limb loss, and neuromuscular disorders, fostering their interaction with educational and therapeutic content.[83]

In medical education, BCIs offer immersive learning experiences by simulating complex neurological conditions.

This enhances our comprehension of brain activity and disorders, deepening understanding of intricate medical concepts. Furthermore, it prepares professionals for clinical BCI applications, thereby enhancing patient care.[15] BCIs also exhibit potential in managing emotional disorders and learning disabilities, indicating broad applicability in medical and psychological education.[84]

BCIs are integral to the continuous professional development of physicians. They facilitate skill enhancement, enable physicians to remain abreast of neurotechnological advancements, and foster understanding of the ethical, legal, and social implications of such technologies in health care.[85] Their adaptability and ongoing refinement align with the dynamic landscape of medicine, offering contemporary diagnostic, treatment, and rehabilitation tools and methodologies.[86]

Additionally, BCIs have shown positive effects on students' attention, working memory, and other cognitive abilities critical in cognitive rehabilitation and educational settings. They enhance visuospatial, social, imaginative, and emotional skills, contributing to a holistic educational approach.[87]

Table 2. Summary of the Main Advantages of Brain-Computer Interfaces Over Other Intelligence Neurotechnologies

Properties:	BCIs	Other Intelligent Neurotechnologies:
Invasiveness[88,90]	Largely noninvasive, with the recorder component involving EEGs placed onto the scalp.	Invasive methods like DBS which penetrate the brain mater to reach a specific area of the brain, spinal cord stimulators and electrical stimulators.
Adaptability[89,91]	Personalized, adaptable solutions; demonstrated promising value for functional restoration in paralysis and stroke survivors.	Invasive nature makes them potentially less adaptable, influencing risk profiles.
Functionality[93,94]	Establishes direct communication between the brain and external devices; a close-loop system.	Open-loop system in some cases, lacking precision and adaptability.
Precision[93-95]	Excel in closed-loop system functionality, thereby being able to measure, estimate, and predict neural activity in order to adjust delivery to reach optimum, therapeutic neural dynamic targets.	Open-loop may lead to imprecise symptom regulation.
Future potential[4,12,90,91,96-99]	Potential for neurorecovery and neurorehabilitation; inducing plasticity and learning.	Promise in specific therapeutic applications but may face challenges in terms of adaptability.

BCI, brain-computer interface; EEG, electroencephalography; DBS, deep brain stimulation.

ADVANTAGES OF BCIs OVER OTHER INTELLIGENT NEUROTECHNOLOGIES

BCIs offer distinct advantages over other intelligent neurotechnologies, including neuromodulators and neuroprostheses. Unlike invasive techniques like DBS or spinal cord stimulators, BCIs are often noninvasive, using scalp-recorded EEG activity, which enhances safety and versatility.[88] BCIs establish a direct communication pathway between the brain and external devices, providing personalized, adaptable solutions, particularly promising for functional restoration in conditions like paralysis.[89]

While neuroprostheses and neuromodulators, including invasive techniques like DBS or spinal cord stimulators, offer specific therapeutic benefits for conditions such as PD, chronic pain, or spinal cord injuries,[90] their invasive nature makes them less adaptable than noninvasive BCIs. This invasiveness is a crucial factor, influencing both risk profiles and the potential for widespread clinical application.[91] Neuroprostheses decoding electrophysiological signals for prosthetic limb or wheelchair control are indicative of BCIs' potential to enhance specificity and adaptability in these domains.[92]

BCIs particularly excel in their closed-loop system functionality, contrasting with the majority of open-loop DBS systems used for conditions like major depressive disorder (MDD). Current DBS methods often lack the capability to track the complex, nonlinear neural dynamics in MDD, leading to imprecise symptom regulation and variable treatment effects.[93,94] Neural mass models have been utilized to simulate MDD's multiband neural dynamics in response to DBS. They developed a dynamic model to optimally adjust DBS, targeting therapeutic neural dynamics.[95] This exemplifies how BCI and artificial intelligence can refine neuromodulation precision.

Looking forward, BCIs show immense promise in neurorecovery and neurorehabilitation, owing to their capacity for inducing plasticity, enhancing learning and remapping, and restoring capacities lost to neurologic injury or disease.[4] Studies demonstrate BCI's effectiveness in these areas, such as experiments on supernumerary robotic finger training revealing cerebellar compensatory mechanisms or research showing improved motor function recovery in stroke survivors following BCI training.[12,96,97] Furthermore, combining BCI-based hand rehabilitation systems with conventional therapy can lead to sustained upper limb improvements in stroke survivors.[98] Additionally, research discovered synergistic gains in cortical activation when combining a soft robotic bilateral hand rehabilitation system with mirror visual feedback,[99] naturalistic, closed-loop systems poised to revolutionize neurotechnological developments.[6,100] **Table 2** provides a comparative summary of the primary advantages of BCIs over other intelligent neurotechnologies.

CHALLENGES WITH USING BCI

Technical Challenges

BCIs confront technical hurdles due to the nonstationary nature of brain signals, which are affected by emotional states like sadness or happiness.[101] Noise, often from competing electrical signals, further challenges the accuracy and reliability of

BCIs.[101,102] The diversity in brain signal patterns across subjects, sessions, and tasks complicates the development of universally effective pattern recognition models.[103] Limited training data for machine learning models exacerbates these challenges, necessitating continuous research for performance enhancement.[103,104] Factors such as cognitive processes, neurophysiology, and individual neurological variations contribute to BCI performance variability.[9,86] Psychological elements like attention, memory load, and fatigue, along with personal attributes, intricately influence brain dynamics.[15,105] BCIs struggle with slow ITRs and user dissatisfaction due to the need for repeated actions. Various factors, including BCI type, signal processing techniques, and user proficiency, affect ITRs.[106-110] Enhancing signal-to-noise ratios is identified as crucial for improving target detection accuracy,[27,111] with various preprocessing techniques employed for signal-to-noise ratio optimization.[112,113]

Usability Challenges

BCI usability challenges revolve around the intensive training required for medical professionals and the alignment of ITRs with user expectations.[9] Users often prefer simpler, easy-to-operate systems, highlighting the necessity for training in the neurosurgical community.[114,115] The demand for continuous mental monitoring in BCIs leads to user fatigue, with attention fluctuations impacting input accuracy.[9] Real-world applications often require mobility, yet BCIs typically restrict user movement during usage. Moreover, the physical discomfort from nonergonomic EEG headsets affects the user experience, emphasizing the need for user-friendly designs adaptable to clinical workflows.[9]

Cost and Affordability

The adoption and scalability of BCI technology in neurosurgery are significantly hindered by its high cost. However, the landscape is evolving favorably due to advancements in consumer-grade technology, offering more affordable options. For instance, products like the Emotiv EEG Neuro-headset and Emotiv EPOC + are paving the way for accessible, high-frequency BCIs with reasonable accuracy.[116,117] Additionally, innovations in BCI-based mobility aids, such as electric wheelchairs, highlight the potential of creating effective solutions at lower costs using off-the-shelf components.[118] Despite these developments, sophisticated systems, especially those requiring extensive electrode setups, remain costly and out of reach for many.[119] Nonetheless, the trend is moving towards more affordable and accessible BCIs, indicating a future of wider adoption and diverse applications.

Safety

Safety stands as the utmost priority in the utilization of BCIs. Ensuring the long-term safety of BCIs is essential, with a minimal risk of adverse effects being paramount. This spans not only the physical safety of the devices themselves but also the security of the data being transmitted and received. Consequently, there are concerns pertaining to the physical and mental safety of users, as invasive procedures may introduce risk factors such as bleeding, infection, and other surgical complications.[86]

Ethical, Legal, and Social Concerns

BCIs raise significant ethical, legal, and social considerations, including issues of consent, especially for those without capacity, privacy, autonomy with stimulating devices, and the repercussions associated with the acquisition and interpretation of brain data.[86,120,121] Neurosurgeons play a central role in both the development and implementation of BCIs. It is essential that these issues are addressed in tandem as these technologies progress, ensuring responsible and beneficial use.[122] Table 3 outlines a variety of challenges that BCIs encounter, from the technical and usability issues that can affect performance and user experience, to the ethical and safety considerations crucial for responsible BCI integration into health care.

DISCUSSION

Perspectives and Acceptability of BCI by Neurologists and Neurosurgeons

There have been very few studies examining the perceptions and acceptability of BCI by neurologists and neurosurgeons. A recent study by Williams et al. (2022) gives a detailed account of neurosurgeons' views in their two-stage cross-sectional international survey.[1] The study found a limited understanding of BCI technology among participants. There was a high level of

Table 3. Challenges in the Implementation and Use of Brain-Computer Interface

Section	Description
Technical challenges[9,15,27,86,101-113]	BCIs face technical challenges due to non-stationary brain signals, influenced by emotional states, noise, and diversity in signal patterns. Limited training data and cognitive, neurophysiological, and psychological factors contribute to performance variability. Slow information transfer rates (ITRs) and user dissatisfaction are also concerns
Usability challenges[9,114,115]	Usability challenges include intensive training requirements for medical professionals, alignment of information transfer rates with user expectations, user fatigue, and physical discomfort from non-ergonomic EEG headsets
Cost and affordability[116-119]	High costs hinder BCI adoption and scalability in neurosurgery. However, advancements in consumer-grade technology are making BCIs more affordable. Innovations in BCI-based mobility aids show potential for lower-cost solutions
Safety[86]	Safety is paramount in BCI utilization, focusing on the long-term safety of devices and the security of transmitted data. Concerns include risks associated with invasive procedures and the overall well-being of users
Ethical, legal, and social concerns[86,120-122]	BCIs raise ethical, legal, and social issues such as consent, privacy, autonomy, and the handling of brain data. Neurosurgeons play a crucial role in addressing these concerns in the development and implementation of BCIs

BCI, brain-computer interface; EEG, electroencephalography.

acceptability for the use of invasive BCIs in rehabilitative medicine and when BCIs were presented as a means to directly improve patient care or outcomes. However, there was more hesitation or divided opinions when BCIs were suggested for nonmedical or enhancement purposes, such as military applications or cognitive augmentation in healthy individuals. Overall, while there was a general optimism about the potential benefits of BCIs, especially in rehabilitative medicine, the study highlighted the need for further education, ethical debate, and regulatory guidance as BCIs continue to develop.[1]

The aforementioned study mirrors findings from another Canadian population-based cross-sectional survey targeting pediatric and adult neurologists, among other physician specialists.[123] This survey uncovered that among neurologists, the majority (83%) had BCI knowledge scores less than 2, indicating a level of knowledge less than 'somewhat familiar'. Regarding clinical applications of BCI, neurologists most frequently identified communication devices, wheelchair control, and computer usage as the top applications with the potential to improve the quality of life for their patients. The survey found that 70% of neurologist participants rated BCI as having high utility in clinical practice, and 81% believed BCI had high potential to improve patient quality of life. Additionally, a significant majority (82%) believed their patients would be open to adopting BCI.[123]

Enhancing BCIs with Artificial Intelligence

Artificial intelligence (AI) has significantly augmented the capabilities of BCIs, particularly in analyzing and decoding neural activities. AI's integration with BCIs has enabled advancements in athletic abilities, mitigation of symptoms in patients with impaired nerve or muscle control, and fostered neurophysiological discoveries.[124] Despite the challenges of a prolonged training period and stringent monitoring required for AI integration, its role is crucial due to the inherent limitations of BCIs. AI's proficiency in decoding neural signals, including pulse, duration, and amplitude, is particularly beneficial in controlling prostheses. While largely in the preclinical stage, this technology is poised to revolutionize mainstream medicine, evidenced by early applications like EEG-based robotic controls enabling paraplegic patients to maneuver wheelchairs through motor imagery.[125] AI's contribution extends to natural language processing, efficiently interpreting EEG-based semantic representations, and computer vision, which could aid in managing eye diseases.[126,127] Furthermore, AI optimizes BCI outputs in real-time, dynamically adjusting based on comprehensive data inputs. This capability is key to advancing BCIs' efficiency and accuracy, potentially enhancing memory or communication in healthy individuals.[124,128]

FUTURE PROSPECTS

The Augmentation of Noninvasive BCIs

Noninvasive BCIs offer a less painful and costly alternative to their invasive counterparts, albeit with sacrifices in temporal and spatial data quality, impacting signal extraction. Such systems require extensive training periods, which highlights their current inferiority in signal interpretation compared to invasive BCIs. However, insights from invasive BCIs could improve noninvasive methods, particularly in interpreting surface recordings.[105,129]

Accessibility and Cost Particularly in Low Resource Settings

The current use of BCIs is largely limited to severe disabilities due to high short- and long-term costs, including implementation and ongoing technical support, respectively.[130] These factors currently preclude widespread adoption in developing nations. A significant setback for BCI implantation in developing nations also lies in the unfamiliarity of advanced computer technology within the general public.[131] Future accessibility hinges on reducing maintenance complexity, broadening user demographics, and demonstrating efficacy to insurance providers. Advances in technology that enhance functionality and reduce maintenance will necessitate new business models for mainstream care integration, offering financial incentives and reimbursement for clinicians.[132]

Improving Technical Challenges in Reliability

Enhancing the reliability of BCIs is critical for their practical application. For BCIs to

Table 4. Overview of Future Prospects in Brain-Computer Interface Development

Future Prospects	Summary
Enhancing the augmentation of non-Invasive BCIs[105,129]	Noninvasive BCIs, offering a less painful and costly alternative to invasive BCIs, face challenges in data quality, necessitating extended training periods and currently inferior in signal interpretation. However, insights from invasive BCIs could enhance non-invasive methods, particularly in interpreting surface recordings.
Improving accessibility and cost in low resource settings[130-132]	BCIs are primarily used for severe disabilities due to high costs and technical support requirements, hindering adoption in developing countries. Future accessibility depends on reducing maintenance complexity, expanding user demographics, and proving efficacy to insurance providers. Technological advancements should align with new business models for healthcare integration.
Improving technical challenges in reliability[133-135]	Enhancing BCI reliability is crucial for practical applications. Future BCIs could benefit from incorporating signals from multiple brain regions and integrating faster sensory inputs. Current limitations confine their use to basic communication for people with severe disabilities.
Addressing privacy and safety concerns[105,136]	As BCIs become more prevalent, robust guidelines and regulations are needed to protect user autonomy and privacy. Challenges include vulnerability to unauthorized data access and the necessity for cryptographic contracts to secure user information.

BCI, brain-computer interface.

be effective, they must match the reliability of natural muscle-based actions.[133] Without improvements, their use might be confined to basic communication functions for people with severe disabilities. Future BCIs could benefit from incorporating signals from multiple brain regions, mimicking the CNS's natural muscle outputs.[134] Additionally, moving beyond visual feedback and integrating faster sensory inputs, such as proprioceptive and cutaneous stimuli, could significantly enhance BCI performance.[135]

Privacy and Safety in BCI Use

The increasing prevalence of BCIs necessitates robust guidelines and regulations to safeguard user autonomy and privacy. The vulnerability of consumer-grade BCIs to unauthorized data access, including password and facial recognition decoding, underscores the need for legal frameworks. Implementing cryptographic contracts within BCIs could ensure user privacy by rendering confidential information unreadable to unauthorized parties.[136] Table 4 summarizes these aforementioned future prospects in BCI development.

CONCLUSION

This review has critically explored the evolving landscape of BCIs in neurology and neurosurgery. Originating from the early 20th century development of EEG, BCIs have advanced to address diverse neurological challenges, offering novel therapeutic and rehabilitative solutions. From aiding communication in ALS and locked-in syndrome patients to enhancing recovery in stroke and SCD cases, BCIs have demonstrated significant clinical potential. However, this burgeoning field confronts challenges such as technical limitations, user training demands, cost constraints, safety considerations, and ethical dilemmas. These issues underline the necessity for further research and innovation, particularly in enhancing noninvasive BCI techniques and integrating AI for improved signal interpretation and application. The future trajectory of BCIs is promising, marked by potential advancements in accessibility, especially in resource-limited settings, and efforts to bolster their reliability and user safety. As BCIs continue to intersect with cutting-edge technology and neuroscience, they hold the promise of significantly enriching patient care and expanding the frontiers of neuroscientific knowledge and application.

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

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