Review Article

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Brain–computer interfaces: the innovative key to unlocking neurological conditions

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Abstract

Neurological disorders such as Parkinson's disease, stroke, and spinal cord injury can pose significant threats to human mortality, morbidity, and functional independence. Brain–Computer Interface (BCI) technology, which facilitates direct communication between the brain and external devices, emerges as an innovative key to unlocking neurological conditions, demonstrating significant promise in this context. This comprehensive review uniquely synthesizes the latest advancements in BCI research across multiple neurological disorders, offering an interdisciplinary perspective on both clinical applications and emerging technologies. We explore the progress in BCI research and its applications in addressing various neurological conditions, with a particular focus on recent clinical studies and prospective developments. Initially, the review provides an up-to-date overview of BCI technology, encompassing its classification, operational principles, and prevalent paradigms. It then critically examines specific BCI applications in movement disorders, disorders of consciousness, cognitive and mental disorders, as well as sensory disorders, highlighting novel approaches and their potential impact on patient care. This review reveals emerging trends in BCI applications, such as the integration of artificial intelligence and the development of closed-loop systems, which represent significant advancements over previous technologies. The review concludes by discussing the prospects and directions of BCI technology, underscoring the need for interdisciplinary collaboration and ethical considerations. It emphasizes the importance of prioritizing bidirectional and high-performance BCIs, areas that have been underexplored in previous reviews. Additionally, we identify crucial gaps in current research, particularly in long-term clinical efficacy and the need for standardized protocols. The role of neurosurgery in spearheading the clinical translation of BCI research is highlighted. Our comprehensive analysis presents BCI technology as an innovative key to unlocking neurological disorders, offering a transformative approach to diagnosing, treating, and rehabilitating neurological conditions, with substantial potential to enhance patients' quality of life and advance the field of neurotechnology.

Keywords: brain–computer interface, disorders of consciousness, neurological conditions, neurosurgery, Parkinson's disease

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Introduction

The Global Burden of Disease Study in 2015 revealed that diseases of the nervous system – excluding stroke, brain and nervous system cancers, and communicable neurological disorders – ranked as the second leading cause of mortality worldwide, responsible for 16.8% of all deaths[1]. In 2017, stroke was identified as the third leading cause of combined death and disability, and the second leading cause of death globally[2]. As most neurological diseases become more prevalent with advancing age[3], the global trend toward an aging population is anticipated to increase the incidence of these conditions due to both population growth and aging[4]. The ramifications of neurological diseases are extensive and multifaceted. Patients often endure significant lifestyle disruptions, resulting in social isolation and psychological distress, while their caregivers face considerable familial and economic burdens. The socio-economic impacts include high medical resource utilization, productivity losses, and financial strains associated with long-term care. Neurological impairments substantially reduce quality of life; stroke survivors may struggle with mobility, comatose patients suffer profound cognitive deficits, and individuals with motor dysfunction experience severe physical limitations. Furthermore, neurological and psychiatric disorders such as depression and schizophrenia cause mood instability, cognitive impairments, and social difficulties. Traditional treatment methods frequently fail to address the complexities of neurological dysfunction adequately, highlighting the urgent need for innovative treatment strategies. In this context, brain–computer interface (BCI) technology has emerged as a pivotal area of contemporary medical research due to its potential for groundbreaking applications[5].

BCI technology represents a groundbreaking domain within neuroengineering, facilitating bidirectional communication between brain activity and machine control by establishing a direct link between the human brain and external devices[6]. Central to this technology is its capability to interpret brain signals in real time, converting them into commands to control external devices, or translating external stimuli into signals that the brain can perceive. Essentially, BCI technology serves as a conduit for transforming brain intentions into actions, thereby augmenting natural human abilities and presenting novel treatment and rehabilitation options for individuals with neurological disorders. BCI technology demonstrates remarkable potential for the diagnosis, therapeutic intervention, and rehabilitation of neurological conditions[7,8]. From a diagnostic perspective, BCIs provide a non-invasive means of monitoring neural activity, offering vital insights into brain functions and pathologies that surpass conventional methods[9]. Therapeutically, BCIs enable the restoration of lost functions by allowing control over prosthetic devices or computer systems solely through thought, circumventing damaged neural pathways. For rehabilitation purposes, BCIs activate specific neural circuits in response to real-time brain activity, fostering neural adaptation and recovery[10,11]. Furthermore, the integration of BCI with emerging technologies such as artificial intelligence (AI) and machine learning enhances the precision and adaptability of these interfaces[12,13]. By learning from users' brain patterns, BCIs become more intuitive and effective, providing personalized therapy tailored to individual neurological profiles. The rapid advancement of artificial intelligence technology, particularly the emergence of ChatGPT[14], has demonstrated its vast potential for applications in the medical field[15], further propelling the development of these cutting-edge technologies.

BCI technology exemplifies the advantages of interdisciplinary collaboration, integrating technological innovation with neuroscience. Neurosurgeons are crucial in electrode implantation, ensuring minimal tissue damage[16]. This field synergizes biomedical engineering, neuroscience, computer science, and AI to analyze neural data and develop algorithms, while material science contributes to enhancing implant safety and stability[17]. Such collaborative efforts propel BCI technology forward, promising substantial improvements in patient quality of life and the treatment of neurological disorders[18]. This paper offers a comprehensive descriptive review of the advancements in BCI research, with a particular focus on the treatment of neurological disorders. The document begins with a thorough review of the developmental history of BCI technology, followed by an exploration of its applications in treating neurological conditions, and concludes with an examination of future research directions. This structure is designed to underscore the evolving pathways and potential advancements within this rapidly advancing field.

HIGHLIGHTS

1. Transformational Potential of Innovative BCI Technology: Brain–Computer Interfaces (BCIs) represent a cutting-edge technological breakthrough, offering unprecedented solutions for diagnosing, treating, and rehabilitating a wide range of neurological disorders. This innovative technology significantly enhances the quality of life for patients with conditions such as Parkinson's disease, stroke, and spinal cord injury.
2. Innovative Applications and Clinical Trials: The review details specific applications of BCIs in clinical settings, including motor restoration in stroke patients and communication aids for individuals with severe motor impairments, supported by evidence from recent clinical trials.
3. Technological Advancements and Interdisciplinary Collaboration: Advances in AI and machine learning enhance BCI adaptability and precision. The interdisciplinary collaboration across neuroscience, engineering, and clinical fields drives forward the innovation and practical implementation of BCI technologies.
4. Ethical and Safety Considerations: As BCIs integrate deeper into clinical practices, addressing ethical concerns regarding privacy, security, and the long-term effects of implants on health becomes crucial. Establishing robust ethical guidelines and safety protocols is emphasized as essential for the future development of BCI technology.
5. *Future Directions and Challenges*: The document outlines potential future advancements in bidirectional interfaces and high-performance BCI, while also acknowledging existing challenges such as the need for standardized protocols and overcoming technical limitations to improve device usability and patient accessibility.

Evolution and classification of BCI

The development of BCI technology has undergone a series of transformative phases, as depicted in Figure 1. These phases are categorized as the Academic Exploration Phase, the Scientific Validation Phase, and the Experimental Application Phase, with a detailed account provided in Supplementary File 1 (Supplemental Digital Content 1, http://links.lww.com/JS9/D262). Each phase has significantly contributed to our understanding and capabilities in directly interfacing with the human brain.

As shown in Figure 2, BCI technology is classified into three categories based on invasiveness: invasive, non-invasive, and semi-invasive. Invasive BCIs involve the implantation of electrodes directly into the cerebral cortex, offering high signal quality and precise control, albeit with surgical risks and biocompatibility issues[19,20]. Non-invasive BCIs utilize external electroencephalography (EEG) electrodes to detect brain signals with minimal risk, making them suitable for preliminary brain function studies and clinical diagnosis, although they have lower signal quality and are susceptible to environmental noise interference[21–23]. Semi-invasive BCIs place electrodes in subdural or subcortical brain regions, providing a balance with higher signal quality than non-invasive methods and lower risks than invasive ones[24,25]. Furthermore, BCIs are classified as

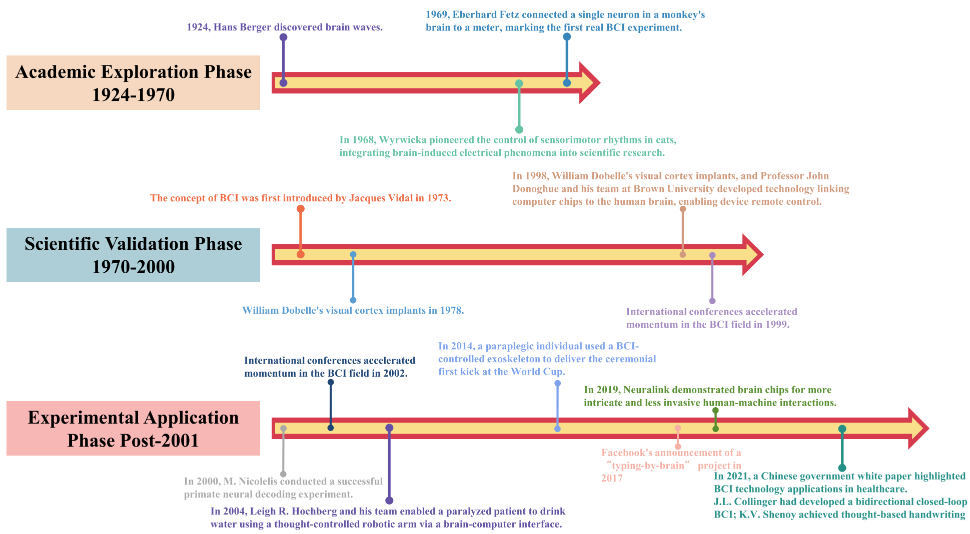

Figure 1. Timeline of the development history of brain–computer interfaces. The timeline is divided into three distinct phases: the Academic Exploration Phase (1924–1970), the Scientific Validation Phase (1970–2000), and the Experimental Application Phase (2001–present). This timeline showcases the progression of BCI technology from initial discoveries in brain wave detection to advanced applications in neural control and human–machine interaction, highlighting key milestones and breakthroughs in the field. BCI, brain–computer interface.

either unidirectional, which transmit signals solely from the brain to a device, limiting feedback and adaptation[16,26], or bidirectional, which enable interactive communication by sending feedback from the device to the brain, thereby enhancing control and response for advanced applications[27]. When selecting a BCI system, it is essential to weigh these characteristics against the specific requirements of patients and the intended applications.

The basic working principle of BCI

The core of BCI technology resides in its ability to capture electrical signals generated by brain activity in real time and convert them into commands that external devices can recognize and execute. This intricate process consists of several stages: brain signal acquisition, preprocessing, feature extraction, feature classification, interface device control, and feedback mechanisms. Notably, the signal processing sequence in BCI systems includes preprocessing, feature extraction, and feature classification, with the latter two being crucial in the effective processing of BCI signals. The operational principles of BCI are illustrated in Figure 2.

Brain signal acquisition

Brain signal acquisition is a fundamental aspect of BCI technology, encompassing the process from capturing brain activity to converting these signals into commands for external devices[28]. EEG is a non-invasive technique that records electrical brain activity via scalp electrodes. It is favored for its non-invasiveness, and high temporal resolution, making it particularly suitable for real-time applications. While EEG can capture neuronal activity in the cerebral cortex, it has limited efficacy for deep brain signals and relatively low spatial resolution[29]. Functional magnetic resonance imaging (fMRI) indirectly reflects neural activity by measuring blood-oxygen-level-dependent signals. It provides detailed anatomical and deep brain activity information with high spatial resolution. However, fMRI equipment is expensive, has low temporal resolution, and is not conducive to portable use, limiting its application in real-time BCI systems[30,31]. Functional near-infrared spectroscopy (fNIRS) measures brain activity using near-infrared light, inferring neural activity through changes in hemoglobin concentration. Compared to EEG, it is less affected by electrical artifacts but has limited penetration depth and is primarily used for studying cortical activity[32]. Magnetoencephalography (MEG) records magnetic fields generated by neurons, providing high spatiotemporal resolution imaging of brain activity. While non-invasive, it is less effective for deep brain signals and requires expensive equipment and specialized shielding[33,34]. Electrocorticography (ECoG) is a semi-invasive technique that places electrodes directly on the brain's surface. It provides clearer signals and higher spatial resolution than EEG but requires surgical implantation and is typically used in clinical settings[35]. Stereoelectroencephalography (SEEG) is another invasive method involving the implantation of electrodes within brain tissue for precise measurement of internal activity. It is crucial for surgical planning and specific BCI applications, providing highly localized neural activity information[36–38]. Each technology has distinct applications and limitations, influencing its role in BCI systems. Selecting an appropriate signal acquisition method requires balancing factors such as signal quality, spatial and temporal resolution, invasiveness, cost, and specific application requirements. For instance, the application of SEEG in epilepsy surgery planning demonstrates its advantage in precisely localizing brain activity. As technology advances, these methods are continuously improving to provide higher quality brain signal data, supporting more sophisticated BCI applications. Future research directions may include enhancing signal quality in non-invasive techniques and developing novel hybrid signal acquisition methods that combine the advantages of different technologies.

BCI system signal processing, decoding, and feedback mechanisms

Preprocessing begins with filtering to remove noise and amplify the brain's faint electrical signals. This step ensures higher signal

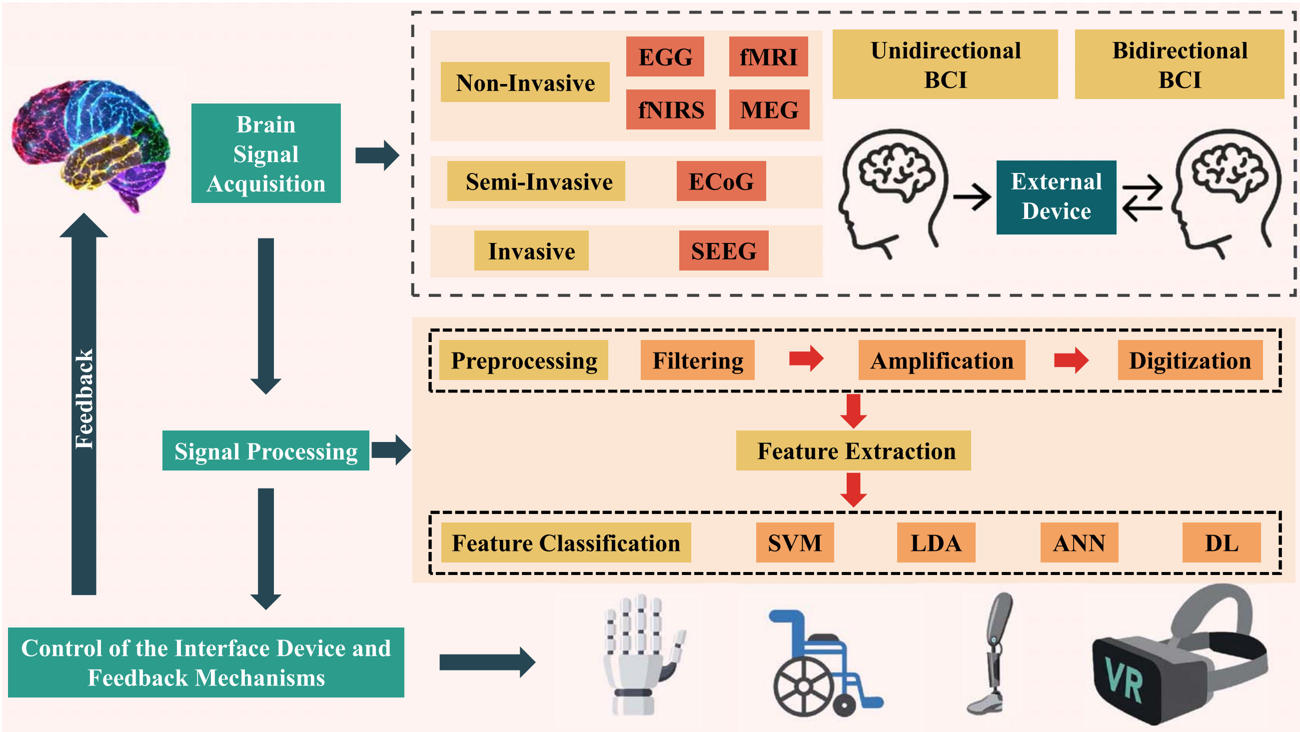

Figure 2. The Classification and Working Principle of Brain–Computer Interfaces. This figure illustrates the comprehensive process and classification of BCI systems, from brain signal acquisition to the control of interface devices and feedback mechanisms. The process begins with brain signal acquisition, which is classified into three categories based on invasiveness: Non-Invasive (including EEG, fMRI, fNIRS, and MEG), Semi-Invasive (utilizing ECoG), and Invasive (employing SEEG). BCIs are further categorized as Unidirectional, where information flows from the brain to an external device, or Bidirectional, allowing information flow in both directions. The acquired signals undergo signal processing, which involves preprocessing (filtering, amplification, and digitization), feature extraction, and feature classification using algorithms such as SVM, LDA, ANN, and DL. The processed signals are then used to control various interface devices, including prosthetic limbs, wheelchairs, assistive devices, and VR systems, which can provide feedback to the user, completing the BCI loop. This comprehensive illustration encapsulates the entire BCI process, highlighting the various methods and technologies involved at each stage and demonstrating the complexity and versatility of BCI systems in bridging the gap between neural activity and external device control. ANN, artificial neural network; DL, deep learning; EEG, electroencephalography; ECoG, electrocorticography; fMRI, functional magnetic resonance imaging; fNIRS, functional near-infrared spectroscopy; LDA, linear discriminant analysis; MEG, magnetoencephalography; SEEG, stereoelectroencephalography; SVM, support vector machine; VR, virtual reality.

fidelity during the analog-to-digital conversion (ADC), thereby improving data quality for subsequent digital processing[39–41]. The core decoding algorithm then transforms these signals into control commands by identifying and classifying task-related features, such as time-domain, frequency-domain, or time-frequency attributes, using machine learning algorithms like Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), or Artificial Neural Networks (ANN)[42–46]. These control commands enable actions like cursor movement, wheelchair control, or prosthesis operation[47–49].

The control of interface devices is critical, with systems such as virtual reality (VR) creating immersive environments where users can manipulate virtual objects and receive real-time feedback, thereby enhancing control and aiding in neurological rehabilitation[50]. Robotics in BCI applications provide physical feedback through devices like robotic arms controlled by imagined movements, enhancing tactile feedback and facilitating system control learning[51–53]. Additionally, haptic feedback devices, such as vibrators or force feedback gloves, help users verify successful actions, improving control accuracy and learning efficiency[54,55]. These feedback mechanisms are essential in BCI systems, aiding in the adjustment of EEG signals during training and fine-tuning the system's interpretation of EEG patterns to optimize performance and accommodate individual differences.

BCI paradigms

BCI technology converts brain activity into commands for controlling external devices, providing innovative treatment and rehabilitation methods for neurological disorders. Motor Imagery-based Brain–Computer Interfaces (MI-BCIs) detect EEG signals during imagined movements, particularly in motor cortical regions, to operate devices such as VR systems for rehabilitation or motorized wheelchairs, and facilitate communication tools like brain-controlled text input by noting changes in μ and β rhythms[57–59]. MI-BCIs are particularly beneficial for stroke or spinal cord injury patients in regaining motor function[60–62] and include applications such as VR systems for rehabilitation, motorized wheelchairs[63,64], and brain-controlled text input[65].

Steady-State Visual Evoked Potentials (SSVEP) exploit visual stimuli at specific frequencies to elicit brain responses, enabling device control through visual fixation on these frequencies, which is utilized in typing systems and interfaces[66–69]. Auditory Evoked Potentials (AEP) use auditory stimuli for control, making them suitable for noisy or dark environments and applicable in devices like hearing aids[70–72]. The P300 paradigm, based on attention to visual stimuli, generates responses to infrequent events and is employed in emergency communication systems[73–75]. Each of these paradigms offers distinct capabilities tailored to user needs, and ongoing technological advancements continue to enhance options for patients with neurological impairments.

Fundamentals of neuroscience

The nervous system, consisting of the central nervous system (CNS) and peripheral nervous system (PNS), plays a critical role in the transmission and processing of information within the body[76]. The CNS, which includes the brain and spinal cord, is responsible for processing information and making decisions. Brain structures such as the cerebral cortex, basal ganglia, thalamus, and cerebellum are involved in managing perception, cognition, emotion, memory, and motor control[77]. The spinal cord serves as a conduit, linking the brain to the body and facilitating the transmission of information and reflex actions. The PNS acts as a communication network between the CNS and the rest of the body, transmitting sensory data back to the CNS.

Neural signals, fundamental to nervous system function, are produced and transmitted by neurons via action potentials. These action potentials are rapid changes in membrane potential caused by ion channel activity[78]. Such changes result in potential differences that trigger the release of neurotransmitters across synapses to the subsequent neuron[79]. Signal transmission within neural circuits ranges from simple reflex arcs to intricate networks involved in cognitive and motor control, with neurotransmitters and receptors playing vital roles in mediating synaptic transmission. A comprehensive understanding of the nervous system's structure and signaling mechanisms is essential for advancing BCI technology and addressing neurological disorders.

Research on BCI in the treatment of neurological conditions

Motor disturbances

Parkinson's disease (PD)

PD is a progressive neurodegenerative condition that impairs motor control, manifesting through symptoms such as tremors, muscle rigidity, bradykinesia, and balance difficulties. It is recognized as the fastest-growing neurological disorder worldwide. Between 1990 and 2015, the prevalence of PD doubled to more than 6 million cases, largely attributed to an aging population. Projections indicate that this number may surpass 12 million by 2040[80]. In China, ~1.7% of individuals over 65 years old are affected by PD, amounting to over 2 million patients[81], with expectations of further increases as the population continues to age. By 2020, PD cases in China were anticipated to exceed 5 million, with estimates suggesting that by 2030, more than half of the global PD patients will be Chinese[82], presenting a significant healthcare challenge and societal burden[83]. Deep Brain Stimulation (DBS) is a well-established neurosurgical intervention for the treatment of PD, while BCIs are emerging as a separate but potentially complementary technology for managing motor disturbances. As neurotechnology advances, there is increasing overlap between certain aspects of DBS and BCI technologies. For instance, some advanced DBS systems, such as closed-loop DBS, have incorporated features conceptually similar to those found in BCIs. These systems can monitor brain activity in real-time and adjust stimulation parameters accordingly, demonstrating a trend towards more adaptive and personalized neuromodulation therapies. While these developments show a convergence of some technical aspects, it's important to note that DBS and BCI still remain distinct technologies with different primary goals and implementation methods[84]. Figure 3 depicts the utilization of BCIs in managing motor disturbances. Additionally, randomized controlled trials (RCTs) examining BCIs for the treatment of movement disorders are encapsulated in Supplementary Table S1 (Supplemental Digital Content 2, http://links.lww.com/JS9/D263).

DBS is utilized to manage movement disorders, including Parkinson's disease, through the implantation of small electrodes in targeted brain regions to modulate neural activity[85]. These electrodes are connected via a wire placed under the scalp to a pulse generator implanted in the chest, allowing clinicians to adjust its output to alleviate symptoms such as tremors and muscle rigidity. The successful implementation of DBS necessitates precise neuroimaging guidance and advanced neurosurgical expertise.

Clinical research has demonstrated that DBS significantly ameliorates motor symptoms in PD patients, including tremors, muscle rigidity, bradykinesia, and balance issues, while also diminishing the need for medication and its associated side effects. In a RCT, the effects of DBS versus Best Medical Therapy (BMT) on patients with advanced PD were compared. The study demonstrated that patients who underwent DBS experienced a significant increase in 'on' time – periods of good motor control without significant dyskinesia – along with marked improvements in motor function and quality of life. This trial highlights the potential of DBS to enhance the quality of life for patients with PD[86]. Another RCT involving early PD patients compared the outcomes of those receiving DBS alongside medical therapy against those receiving medical therapy alone[87]. The Parkinson's Disease Questionnaire-39 (PDQ-39), a tool designed to evaluate the quality of life in PD patients, scored from 0 to 100, with lower scores indicating better quality of life, revealed notable improvements. The experimental group showed a substantial enhancement in quality of life (QOL), with PDQ-39 scores increasing by 7.8 points, contrasting with a 0.2-point decrease in the control group. Additionally, the DBS group exhibited greater reductions in motor deficits, improved daily living activities, and fewer levodopa-induced motor complications. The daily levodopa equivalent dose was reduced by 39% in the DBS group, whereas it increased by 21% in the control group. Therefore, DBS surpasses medication alone in early PD treatment, potentially offering a viable option for improving QOL and motor function. Further investigations revealed that patients with poorer baseline QOL experienced more significant improvements following subthalamic nucleus DBS (STN-DBS)[88]. Another study examining the effects of STN-DBS at varying frequencies on upper limb motor function in PD patients found that an 80 Hz frequency notably enhanced performance in assembly tasks. Higher frequencies were effective in reducing rigidity and tremor but had no significant impact on bradykinesia[89].

Research may also focus on developing personalized DBS treatment plans. With more precise neuroimaging and neurophysiological assessments, physicians can customize the optimal

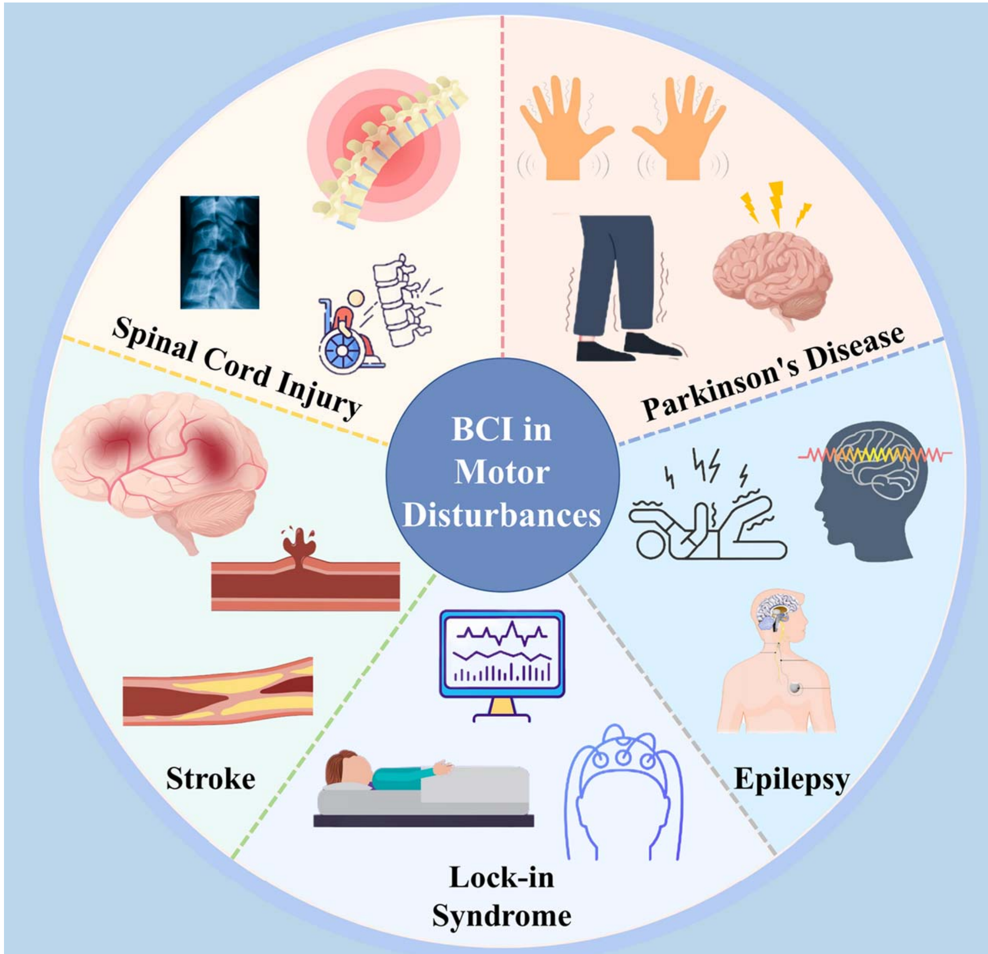

Figure 3. BCI in Motor Disturbances. This circular diagram illustrates the applications of Brain–Computer Interface (BCI) technology in various motor disturbances. Centered on 'BCI in Motor Disturbances,' the figure showcases five major neurological conditions: Spinal Cord Injury (depicted by spinal X-ray and wheelchair images), Parkinson's Disease (illustrated with trembling hands and brain activity), Epilepsy (represented by brain activity patterns and monitoring equipment), Lock-in Syndrome (shown with a bedridden patient and brain signal monitor), and Stroke (depicted with brain and blood vessel imagery). Each section visually represents how BCI can aid in restoring motor function, managing symptoms, predicting seizures, providing communication channels, and assisting in rehabilitation, respectively. This comprehensive visualization underscores BCI technology's versatility and potential impact in addressing a wide range of motor disturbances, highlighting its transformative role in neurology and rehabilitation medicine. BCI, brain–computer interface.

electrode placement and stimulation parameters for each patient, thereby improving treatment outcomes, reducing unnecessary stimulation, and lowering the risk of complications. The advancement of remote monitoring technology will make treatment more intelligent and convenient. Remote monitoring technology allows physicians to remotely assess the patient's condition and adjust the treatment plan if necessary, thus reducing the number of visits, alleviating patient burden, and enhancing the flexibility and convenience of treatment.

Future advancements in DBS technology include the development of closed-loop systems. These systems are designed to automatically adjust treatment parameters based on real-time brain signal feedback, thereby enhancing the personalization and efficacy of the treatment. This method holds the potential to significantly decrease drug dependency and provide longer-lasting, more autonomous symptom management for PD patients. Research indicates that dopamine medications and DBS exhibit distinct inhibitory effects on subthalamic beta wave activity, and their combination optimizes motor performance, validating their use as feedback signals for closed-loop DBS[90]. Additionally, the therapeutic effectiveness of single-threshold adaptive DBS (aDBS) is significantly influenced by the selection of parameters, motor state, and the controllability of β activity, emphasizing the necessity of optimizing these elements within closed-loop systems[91].

Future research may also focus on creating personalized DBS treatment plans. With advancements in precise neuroimaging and neurophysiological assessments, physicians can tailor the optimal electrode placement and stimulation parameters for each individual patient, enhancing treatment outcomes, minimizing unnecessary stimulation, and reducing the risk of complications. The progression of remote monitoring technology will further enhance the intelligence and convenience of treatment. This technology enables physicians to remotely assess patient conditions and modify treatment plans as needed, thereby decreasing the frequency of clinic visits, reducing patient burden, and increasing the flexibility and convenience of treatment.

Stroke

Stroke, an acute neurological condition, arises from the abrupt rupture or blockage of cerebral blood vessels, culminating in damage to brain tissues. This damage frequently precipitates dysfunctions in motor, sensory, and cognitive abilities[92–94]. Annually, ~15 million individuals globally suffer from a stroke, with one-third succumbing to death and another third experiencing significant disabilities[95]. The primary objective of rehabilitation is to assist patients in recovering functional abilities, enhancing life quality, and maximizing their independence.

Motor imagery training, a rehabilitation technique, involves patients visualizing specific bodily movements[96]. During such sessions, participants are instructed to mentally simulate actions like grasping with a hand or walking with legs, utilizing brain plasticity to aid in the reformation of neural pathways[97]. Brain–Computer Interface (BCI) technology detects these imagined movement patterns and transforms them into operational signals for external devices, thus augmenting the efficacy of motor imagery training. In a RCT involving 28 subacute stroke patients, the impact of BCI-enhanced motor imagery training was compared with conventional motor imagery training without BCI support[98]. Findings demonstrated that individuals in the BCI-supported group achieved notably superior functional recovery. Electroencephalography (EEG) data revealed significant enhancements in brain activity pertinent to motor imagery within the BCI group, especially in the desynchronization of alpha and beta bands in the ipsilateral hemisphere. Consequently, BCI technology not only amplifies the therapeutic results of motor imagery training but also boosts patient self-efficacy and motivation for rehabilitation through real-time feedback and the manipulation of external apparatuses.

The BCI system functions by interpreting brain signals associated with motor intentions and mental rehearsals, converting these into commands that enable the intentional manipulation of external devices. This technology capitalizes on learning-induced neural plasticity, which includes modifications in neuron tuning, strengthening of synaptic connections via Hebbian mechanisms, and the activation of related neural networks. By delivering instantaneous feedback and cues, BCI systems are instrumental in improving both motor and cognitive rehabilitation, thereby potentially enhancing motor skills and cognitive capabilities in individuals suffering from stroke or other neurological disorders[99]. Consequently, the integration of BCI technology with motor imagery training and additional rehabilitation methodologies represents a promising avenue for augmenting outcomes in neurorehabilitation, facilitating the recovery of motor and cognitive functions.

BCI systems transform neural activity into operational signals for external apparatuses, such as prosthetic limbs or wheelchairs, through sophisticated signal processing and decoding techniques. For instance, when a patient envisages arm movement, the BCI system identifies particular EEG patterns corresponding to this intent and converts them into commands that activate an external device to execute the envisioned action. This mechanism not only facilitates rehabilitation but also potentially boosts the patient's daily independence by enabling autonomous operation of devices like wheelchairs and prosthetic limbs. A recent investigation introduced a hybrid brain–computer interface (hBCI) that utilizes both EEG and EOG signals for commanding a unified system of a wheelchair and robotic arm[52]. This system merges motor imagery with eye movement data, allowing precise control over both the wheelchair's direction and the robotic arm's grasp. During the evaluation, 22 subjects participated, and five successfully executed a complex task involving autonomous beverage consumption, highlighting the hBCI system's high accuracy and utility for intricate tasks. The findings indicate that the hBCI system markedly enhances the precision and dependability of controlling multiple devices simultaneously, offering novel avenues for increasing patient autonomy in routine activities.

BCI technology holds considerable promise for enhancing cognitive functions in stroke patients, particularly through its application in cognitive assessments and training aimed at improving memory capabilities via neurofeedback[100]. Studies have demonstrated that a BCI system, by leveraging theta and alpha brain waves linked to memory encoding, can substantially boost memory functions by timing the display of items during memory tasks. Furthermore, a BCI setup that combines motor imagery with logic and memory training has been shown to effectively enhance both memory and cognitive skills in older adults. This evidence underscores the substantial potential of BCI technology not only in augmenting working memory but also in advancing other cognitive functions, particularly within the realm of cognitive rehabilitation for stroke survivors.

Spinal cord injury

Spinal cord injury (SCI) is characterized by damage to the spinal cord's structure or function, typically resulting from external forces such as traffic accidents, falls, or sports injuries, or from diseases like myelitis[101]. Globally, the incidence of SCI ranges from 3.6 to 195.4 cases per million people[102], with injuries classified as either complete or incomplete. Complete SCI disrupts all neural transmissions within the spinal cord, leading to a total cessation of motor and sensory functions below the point of injury. Conversely, incomplete SCI maintains partial neural activity, permitting some degree of sensory and motor function retention.

In the realm of SCI rehabilitation, BCIs are primarily deployed to rejuvenate functions in the upper and lower limbs[103,104]. BCIs facilitate motor activity and bolster neuroplasticity – the brain's capacity to form new neural connections – by controlling devices like robotic arms or electrical stimulation systems. Recent clinical trials and case studies validate BCI's efficacy in SCI rehabilitation. Research indicates that multimodal BCIs can enhance movement in the lower limbs and alleviate pain among SCI patients[101], while BCI-assisted motor imagery training significantly boosts upper limb functionality, particularly during initial treatment phases[105]. Furthermore, advanced BCI systems employing implanted microelectrode arrays enable precise control of bionic limbs, enhancing operational accuracy and flexibility. This not only underscores the potential of BCIs to improve daily life and quality of life for SCI patients but also illustrates the practical benefits and effectiveness of BCI technology in fostering patient independence and well-being[106].

Despite progress in the application of BCI for SCI rehabilitation, obstacles such as technical challenges, patient variability, and issues with long-term integration curtail their broad adoption. A review in *Nature Reviews Neuroscience* highlights that while intracortical interfaces have advanced, the invasiveness of these procedures poses significant barriers[107]. Future enhancements in technology and algorithms are anticipated to improve the efficacy of BCIs. Progress in developing minimally invasive systems, tailoring treatments to individual needs, and fostering interdisciplinary collaborations, as well as incorporating virtual and augmented reality technologies, is poised to significantly broaden the scope of BCI applications in rehabilitation.

Lock-in syndrome

Locked-in syndrome is a rare neurological disorder characterized by the retention of consciousness coupled with an almost complete inability to control body movements or communicate verbally or physically with the external world[108]. Typically, this condition arises from damage to the brain stem or midbrain, particularly affecting the nerve fibers in these regions, which disrupts the transmission of nerve signals between the brain and the body. It involves intricate neural networks that are essential for both movement control and sensory input reception.

BCI technology provides an innovative communication and interaction solution for individuals with locked-in syndrome. Utilizing EEG or other non-invasive sensors, BCI technology interprets the user's intentions and translates them into commands for external devices, thus facilitating the independent operation of tools such as wheelchairs or computers. Recent advancements include the integration of an eye-tracking system with sophisticated Hidden Markov Models (HMM) and Deep Neural Networks (DNN), significantly enhancing the precision of character recognition and input speed. Consequently, these improvements allow patients with locked-in syndrome to communicate more effectively using eye movements, promoting more fluid interaction.

BCI technology, while still in the experimental phase, has demonstrated potential in clinical trials for improving communication and quality of life in patients with severe movement disorders. Recent research indicates that integrating BCI with functional electrical stimulation (FES) may enhance both communicative and motor capabilities[109]. Additionally, employing fMRI to identify the most effective locations for ECoG electrode placement can increase BCI effectiveness, particularly in assisting patients with locked-in syndrome in interacting with their surroundings[110]. A comprehensive investigation presents a detailed methodology and standardized procedures for the deployment of implantable BCI[111], from the recruitment of patients to the implantation of the system, illustrating the potential for BCI technology to make significant inroads in health care.

Epilepsy

Epilepsy is characterized as a paroxysmal disorder stemming from the abnormal and synchronous activation of neurons repeatedly[112]. Its origins can be attributed to genetic predispositions, traumatic injuries, tumors, and occasionally, unidentified causes. Typically, it manifests with symptoms such as altered consciousness, convulsions, autonomic nervous system malfunctions, and mild distraction. In more severe instances, it may also involve cognitive and behavioral alterations, which vary in type and intensity among individuals[113].

In epilepsy research, BCI technology primarily concentrates on the detection of neural signals, predicting seizures, localizing seizure origins, and developing closed-loop stimulation treatments. Techniques for neural signal detection encompass traditional EEG and its enhanced variants, such as prolonged video EEG monitoring and functional magnetic resonance imaging (fMRI). Utilizing machine learning algorithms, researchers construct epilepsy prediction models from neural electrical signals, facilitating early seizure warnings. Advanced imaging technologies provide precise localization of seizure foci. Efforts in closed-loop stimulation treatments are directed toward real-time seizure signal detection and the subsequent activation of systems for neural modulation or drug release to mitigate seizures. Observations reveal a critical phase coupling among micro-ECoG signals and cortical neuron discharges, influenced by factors such as brain state, spatial separation, cortical architecture, and external stimuli[114]. This insight is pivotal for deciphering the genesis of ECoG signals and enhancing BCI technology. Smith (2005) acknowledges the limitations of EEG in epilepsy management, such as its partial spatial and temporal coverage, yet underscores its indispensable role in diagnosing, classifying, and managing epilepsy, due to its ability to demonstrate the physiological signs of abnormal cortical excitability and its affordability and convenience[115]. Hence, the value of EEG as a tool for detecting neural signals in epilepsy research remains significant.

A recent investigation has confirmed that bidirectional brain–machine interfaces capable of neural stimulation have shown efficacy in enhancing seizure control in patients with refractory epilepsy, although the underlying therapeutic mechanisms remain to be elucidated[116]. Systems like responsive neurostimulation (RNS) have been shown to foster seizure control through long-term modulation of the activity within epileptic networks, rather than simply suppressing seizures directly. This highlights the potential central role of neuroplasticity in the therapeutic response of epilepsy treatments. Moreover, a novel development in the form of a wireless neural prosthesis (ECOGIW-16E) has been documented to provide prolonged electrocorticography (ECoG) recordings and direct cortical stimulation (DCS) for up to 6 months, with its safety and effectiveness validated in experiments involving non-human primates[117]. This device enhances the precision of seizure focus localization and opens new avenues for closed-loop seizure management and BCI applications. Additionally, a memristor-based system for neural signal analysis, which processes signals in the analog domain, has demonstrated a high accuracy of 93.46% and a nearly 400-fold increase in power efficiency over leading CMOS systems[118], showcasing its significant potential for efficient neural signal analysis in BCI technology.

Despite these advancements, challenges persist in the field of BCI for epilepsy treatment. Issues such as the accuracy of signal detection and decoding, the safety and biocompatibility of long-term implants, and the optimization of parameters for electrical stimulation or drug release for enhanced therapeutic outcomes are critical. Moreover, bridging the gap between laboratory research and clinical practice remains a formidable challenge in the current research landscape.

Disorders of consciousness (DoC)

DoC, which include conditions such as coma, vegetative state (VS), and minimally conscious state (MCS), present varying levels of awareness and responsiveness in patients, posing considerable challenges for their diagnosis, treatment, and rehabilitation[119]. BCI technology has recently facilitated novel approaches to

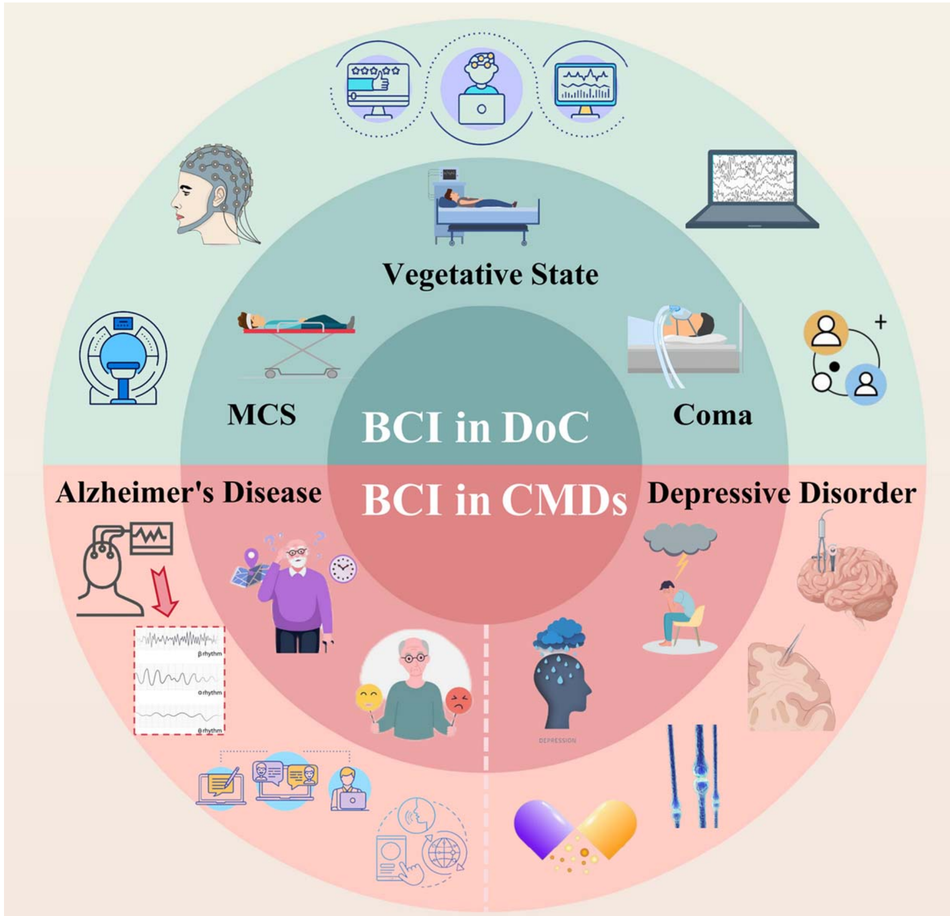

Figure 4. BCI in DoC and CMDs. This circular diagram illustrates the applications of BCI technology in DoC and CMDs. The upper half of the circle depicts BCI in DoC, showcasing three main conditions: Vegetative State, Minimally Conscious State, and Coma. These are represented by images of patients in hospital beds, along with brain monitoring equipment and EEG patterns, highlighting BCI's role in assessing and potentially communicating with patients in these states. The lower half focuses on BCI in CMDs, specifically featuring Alzheimer's Disease and Depressive Disorder. For Alzheimer's, the diagram shows elderly patients, brain activity patterns, and cognitive assessment tools, indicating BCI's potential in early diagnosis and cognitive enhancement. The Depressive Disorder section includes imagery of mood fluctuations, brain stimulation, and medication, suggesting BCI's applications in mood monitoring and treatment. Surrounding these central themes are icons representing various BCI technologies and applications, such as brain signal processing, neural interfaces, and data analysis, emphasizing the comprehensive approach of BCI in addressing these complex neurological and psychiatric conditions. This integrated visualization effectively demonstrates the versatility and potential impact of BCI technology across a spectrum of consciousness disorders and cognitive/mental health challenges. BCI, brain–computer interface; CMDs, Cognitive and Mental Disorders; DoC, Disorders of Consciousness; MCS, minimally conscious state.

understanding, diagnosing, and potentially treating these complex conditions, as illustrated in Figure 4.

Traditional diagnostic methods for DoC primarily depend on behavioral assessments, which are subjective and susceptible to errors. It is reported in the literature that conventional clinical diagnoses, based largely on daily observations, often overlook subtle indicators of consciousness, leading to misdiagnoses of up to 43% of patients as being in a VS[120]. BCI technology, leveraging fMRI and EEG, offers a more objective and reliable means of assessing brain activity in patients with DoC. These technologies are capable of revealing residual cognitive functions and levels of consciousness that may not be detected through conventional behavioral assessments. fMRI, for instance, has been shown to identify volitional brain activities in patients with VS and MCS, particularly those with traumatic brain injuries, indicating some level of awareness and cognitive capability. While promising, the definitive diagnostic and prognostic applications of neuroimaging technologies require further validation to ensure they do not mislead clinical interpretations[121]. Additionally, EEG-based BCI has been shown to discern potential awareness in patients diagnosed with VS by detecting their responses to commands in motor imagery tasks. This method is notable for its affordability and portability, offering a crucial means of assessing consciousness in settings where fMRI is unavailable[122].

EEG-based BCIs have been utilized to detect covert consciousness by identifying event-related potentials (ERPs) in response to auditory or visual stimuli. According to the literature, EEG technology can evaluate the consciousness state of patients with disorders of consciousness by analyzing both early and late ERPs, along with local and global brain activities and spectral analysis[123]. These techniques have shown excellent capability in differentiating between VS and MCS patients. Moreover, the implementation of automated classification systems has enhanced the reliability of diagnoses, aiding in more precise treatment decisions, increasing diagnostic accuracy, and providing crucial insights into patients' cognitive statuses, thereby supporting more tailored care plans.

Among the most notable advancements in BCI for disorders of consciousness is the development of systems that enable communication with patients who otherwise appear unresponsive. BCIs can convert neural signals into actionable commands, allowing patients to deliver simple yes/no responses or control external devices, thus enhancing their quality of life and assisting healthcare providers in understanding patient needs and preferences. Research has demonstrated that P300 spellers, by capturing P300 event-related potentials when patients direct their attention to specific letters or symbols, enable MCS patients to communicate in restricted ways with the external environment. This method offers vital information about their remaining cognitive functions. By concentrating on particular letters or symbols displayed on a screen, patients can produce distinctive brain responses, which a BCI system then interprets to spell out words. This technique marks a significant step forward, enabling patients with MCS to convey their thoughts and interact more meaningfully with their surroundings[124].

BCI technology has been investigated for its potential in rehabilitating patients with disorders of consciousness. By offering real-time feedback on brain activity, BCI systems are able to facilitate the restoration of neuroplasticity and cognitive functions[125]. Moreover, when combined with neurofeedback training, BCI has demonstrated potential for enhancing cognitive abilities in these patients. Neurofeedback training involves monitoring brain activity and providing feedback, enabling patients to learn to control their brain wave patterns. Research suggests that EEG-based neurofeedback training can significantly bolster attention and memory capabilities in patients, while also yielding more objective data. This facilitates the development of customized care strategies and supports the enhancement of neuroplasticity and cognitive function recovery[126].

Cognitive and mental disorders

Alzheimer's disease (AD)

AD is identified as a progressive neurodegenerative disorder, primarily marked by memory deterioration, cognitive decline, and behavioral disturbances. As the global population ages, the prevalence of AD is escalating, thereby exerting a substantial impact on individuals, families, and societal structures[127]. Figure 4 demonstrates the role of BCIs in addressing cognitive and mental disorders. Furthermore, Supplementary Table S2 (Supplemental Digital Content 3, http://links.lww.com/JS9/D264) offers an exhaustive overview of research studies that investigate the efficacy of BCIs in the management and treatment of these disorders.

Research on BCI technology in the management of AD primarily targets early diagnosis, symptom management, therapeutic interventions, and cognitive rehabilitation. These investigations deploy innovative technological methods to enhance patients' life quality, decelerate the progression of the disease, and pioneer non-pharmacological treatment avenues. The timely detection of AD is pivotal for initiating effective interventions and mitigating the advancement of the condition. While traditional diagnostic approaches largely depend on clinical symptomatology and neuroimaging, they tend to recognize the disease at a more advanced stage. Dubois *et al.*[128] have highlighted that conventional diagnostics suffer from delays, high biomarker variability, limited imaging sensitivity, and results affected by multiple variables. In contrast, BCI technology facilitates early diagnosis by capturing and analyzing EEG signals to identify early neural activity changes[129,130]. For instance, abnormalities in specific EEG frequency bands, like theta and alpha waves, during cognitive tasks in AD patients can indicate early disease presence. Prichep *et al.*[131] have shown that quantifying such EEG characteristics, especially increased theta power, can predict future cognitive decline effectively. This method demonstrates high sensitivity and specificity for detecting potential cognitive deterioration in normal elderly individuals, thus bolstering early detection and intervention strategies in AD. Additionally, recent studies have investigated the potential of non-invasively monitoring AD progression through ultra-weak photon emission from the hippocampus, suggesting the development of minimally invasive BCI photon chips as innovative tools for AD diagnosis and monitoring[132].

In recent times, the integration of BCI technology into the treatment and cognitive rehabilitation for AD has garnered widespread interest, notably enhancing symptom management and patient quality of life. BCI facilitates symptom relief through neural modulation techniques, including neurofeedback training that adjusts brain electrical activity, thus improving mood and reducing symptoms of anxiety and depression. Additionally, BCI can be integrated with other therapeutic interventions like Transcranial Magnetic Stimulation (TMS) and FES to amplify the therapeutic outcomes. Research has indicated that BCI-driven neurofeedback training can either stabilize or augment cognitive functions in AD patients, particularly enhancing memory and recall capabilities[133]. An initial study investigated neurofeedback training's efficacy in boosting visual attention and reading abilities in patients with mild Alzheimer's, positing this approach as a novel direction for non-pharmacological AD treatment[134]. Furthermore, a recent investigation proposed a BCI model based on classical conditioning and brain state classification for AD patients, linking thoughts of 'yes' and 'no' with emotional stimuli to aid basic communication and cognitive rehabilitation. This study presents innovative methods and potential uses for BCI in cognitive rehabilitation[135].

Depressive disorder

Depression represents a prevalent and severe psychological disorder, for which conventional interventions like pharmacotherapy and psychotherapy yield insufficient results in certain individuals. The direct engagement of BCI technology with neural processes introduces an innovative potential therapeutic strategy, especially employing DBS and EEG-based systems.

In the domain of depression treatment, BCI technology and DBS represent two different but potentially complementary approaches. While BCI typically involves non-invasive or minimally invasive methods to interpret and modulate brain activity DBS is an invasive technique that involves the implantation of electrodes into targeted brain regions such as the amygdala or the subgenual cingulate cortex, offering potential benefits for individuals suffering from treatment-resistant depression. Despite the surgical risks linked to DBS, it represents a valuable alternative for those unresponsive to traditional treatments. A significant investigation into this area involved a multicenter, randomized, sham-controlled trial assessing the safety and efficacy of DBS within the subcallosal cingulate region for treatment-resistant depression[136]. The findings revealed that improvements were observed in both the actively stimulated and sham groups over a 6-month period, yet no significant differences in response rates were detected. The trial also confirmed the safety and feasibility of subcallosal cingulate DBS, prompting the need for further research to establish its antidepressant effectiveness. Additionally, another study used a CUMS mouse model to explore the therapeutic effects of DBS in the nucleus accumbens (NAc)[137]. The study demonstrated that prolonged and repeated NAc-DBS significantly reduced depressive-like behaviors in CUMS mice, primarily through the increase of gamma-aminobutyric acid (GABA) levels in the ventral tegmental area, thus alleviating inhibition of dopamine neurons. This result provides new neurobiological evidence supporting the application of NAc-DBS in the treatment of treatment-resistant depression. More recently, a study investigated the safety and clinical efficacy of bilateral habenula (HB) DBS in treating treatment-resistant depression[138]. Conducted as a prospective, open-label trial, the research involved HB-DBS surgery on seven patients with treatment-resistant depression or bipolar disorder, demonstrating significant reductions in depressive and anxiety symptoms. At the 1-month follow-up, reductions of 49% in symptoms were noted, with clinical improvements maintained through the 3-month, 6-month, and 12-month follow-ups. The study also discovered a correlation between HB oscillatory activity and the severity of depressive and anxiety symptoms, further underscoring the importance of HB dysfunction in the pathophysiology of depression.

EEG-based BCI systems have been increasingly recognized for their adjunctive role in the treatment of depression. These systems function by monitoring and interpreting specific brainwave patterns, offering feedback that assists patients in managing their emotional and cognitive symptoms, thereby mitigating depressive manifestations. Additionally, EEG-based BCIs are capable of categorizing and evaluating depression in patients by real-time analysis of particular frequency bands and electrodes. A particular study utilizing an EEG-based BCI system unveiled novel uses for BCI in the therapeutic management of depression[139]. This research employed residual neural networks (ResNets) to process EEG data, improving the accuracy of classification and scoring by focusing on specific frequency bands and cerebral areas. The findings revealed that brain waves within the beta band were particularly effective in distinguishing depression, and the channels chosen were adept in assessing the severity of depression. This technology not only facilitates the detection of depression but also offers a quantitative scoring of symptoms, enhancing personalized treatment approaches and monitoring of patient progress. Further research examined the impact of psychoneurotherapy (PNT) on EEG activity in patients with major depressive disorder (MDD)[140]. In this study, BCI-enabled PNT combined with real-time EEG feedback was used to empower patients to self-regulate their brain activity. Results indicated a significant reduction in high-beta (18–30 Hz) activity in the prefrontal cortex post-treatment, which corresponded with notable alleviation of depressive symptoms.

Sensory disorders

Auditory disorder

Auditory disorders impact millions globally, severely affecting communication abilities and overall quality of life. Hearing impairments, characterized by various dysfunctions in the auditory system, hinder the ability to perceive sounds. These impairments may result from damage to any part of the auditory pathway, including the outer, middle, and inner ear, or the auditory nerve, along with abnormalities in the brain areas responsible for processing sound. In response, BCI technology presents innovative approaches by directly interfacing with the auditory system to enhance hearing capabilities. Recent advancements in this field have demonstrated considerable promise in improving auditory perception and facilitating more effective communication. Notably, Figure 5 illustrates the utilization of BCIs in treating sensory disorders, while Supplementary Table S3 (Supplemental Digital Content 4, http://links.lww.com/JS9/D265) provides an extensive review of research on the effectiveness of BCIs in managing and treating these conditions.

Auditory BCI systems employ EEG signal analysis to offer alternative communication and control mechanisms that bypass conventional auditory routes. For instance, Kanoh *et al.*[141] developed a BCI system based on auditory stream segregation with ERP to identify the chosen auditory stream, achieving detection accuracy as high as 95%. Research by Nijboer *et al.*[142] verified the practicality of using P300-evoked potentials within auditory BCI settings. These studies have indicated that BCIs based on P300 potentials can facilitate consistent communication for patients with ALS, including those with compromised visual functions. Such systems are particularly advantageous for hearing-impaired individuals as they decipher essential information from EEG signals when the user concentrates on specific auditory cues. Moreover, Huang *et al.*[143] investigated various auditory paradigms in spatial auditory BCIs, comparing musical notes to beeps, finding that BCIs using frequency-specific beep paradigms significantly exceeded those utilizing musical scales in accuracy. This finding supports the notion that refining auditory stimulus paradigms could enhance BCI applications for the hearing impaired. Additional research demonstrated that integrating ASSR with P300 in a hybrid auditory BCI paradigm substantially enhances both detection accuracy and overall system performance[144]. This hybrid approach combines the selective attention facilitated by P300 potentials with ASSR's frequency tracking, enabling BCI systems to operate with heightened efficiency and stability in diverse settings.

Vision disorder

Visual impairment encompasses any condition that diminishes an individual's capacity to process visual stimuli, which may affect aspects such as vision, visual field, contrast sensitivity, color perception, and depth perception. The clinical symptoms associated with visual impairment can include reductions in visual acuity, losses in visual field, anomalies in color vision, decreased contrast sensitivity, and impairments in depth perception. Research into BCI technology for visual impairment primarily investigates applications such as high-frequency SSVEP-based BCIs that integrate with computer vision to facilitate the control of robotic arms for specific actions. This system is capable of identifying and pinpointing objects within a working environment, enabling users to select and manipulate objects via BCI for automated tasks such as grasping and placing. Such sophisticated

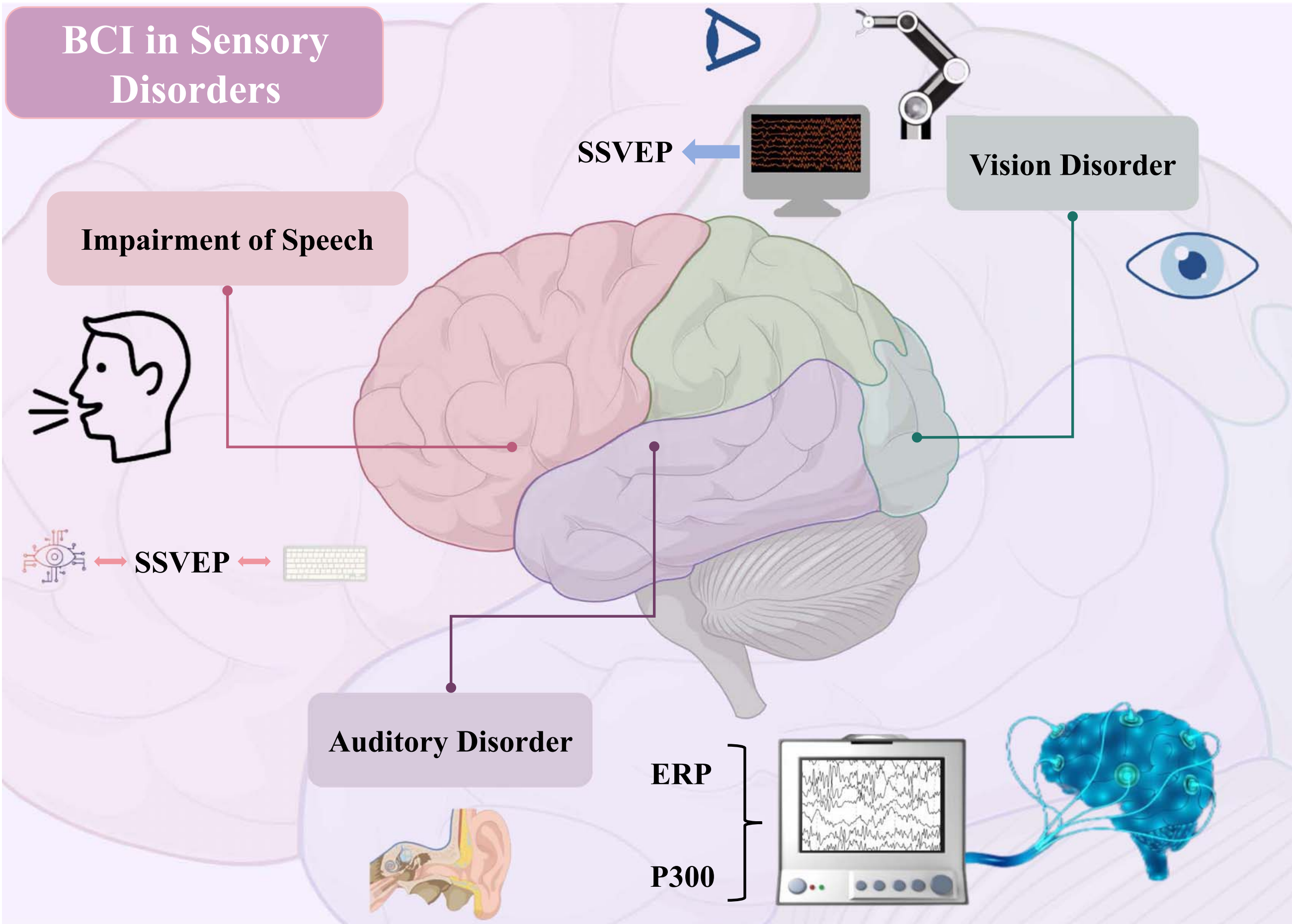

Figure 5. BCI in Sensory Disorders. This figure depicts the application of BCI technology in various sensory disorders, including auditory disorders, vision disorders, and speech impairments. For auditory disorders, BCI systems utilize EEG signal analysis and multiple paradigms, such as auditory stream segregation with ERPs, P300-evoked potentials, and ASSR, to provide communication and control methods that complement or serve as alternatives to conventional auditory pathways; In the context of vision disorders, BCI research involves various methods, primarily including high-frequency SSVEP, P300, and SCP. For example, SSVEP-based BCIs integrated with computer vision can be used to control robotic arms for specific tasks, enabling users to manipulate objects in their environment; For speech impairments, BCI technology offers solutions tailored to different types of disorders (such as motor aphasia, sensory aphasia), through techniques including eye-tracking, SSVEP-based BCIs, silent speech recognition, and speech synthesis. These approaches aim to restore communication abilities and enhance the quality of life for individuals with language disorders; It should be noted that many of these technologies are still in the research phase and may face challenges and limitations in clinical applications. As technology continues to advance, these methods are expected to provide more effective assistance to patients with sensory disorders in the future. ASSR, auditory steady-state responses; BCI, brain–computer interface; ERP, event-related potential; SSVEP, steady-state visual evoked potentials.

control mechanisms significantly lessen the operational demands on the user while enhancing the precision and efficiency of task performance[145]. Presently, the deployment of BCI technology for treating visual impairments remains predominantly experimental.

Impairment of speech

Speech impairment, such as aphasia and language comprehension disorders, arises from brain damage and hampers effective communication. BCI technology offers innovative communication and rehabilitation solutions for these individuals. Studies exploring the utility of eye-tracking and SSVEP (steady-state visually evoked potentials) BCI in patients with advanced-stage Amyotrophic Lateral Sclerosis (ALS) and visual impairments have demonstrated that integrating enhanced eye-tracking with SSVEP BCI and the Shuffle Speller interface can improve communication capabilities, although typing accuracy exhibits considerable variability among participants[146]. Current research is also focused on silent speech recognition and speech synthesis technologies[147]. Silent speech recognition involves decoding neural signals that are produced without vocalization to recognize intended speech, whereas speech synthesis converts these decoded signals into audible speech. This research underscores the application of machine learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), in refining the precision and reliability of BCI systems. A study published in *Nature* confirmed the high efficiency and stability of a BCI system capable of decoding speech commands over a period of 3 months without needing recalibration, thus affirming the practical viability and effectiveness of BCI technology[148]. Further investigations have looked into long-term implanted BCIs for speech synthesis, where ECoG (electrocorticography) signals are decoded into synthetic speech using RNNs. Results indicated that ALS patients could produce intelligible speech recognized accurately by listeners in most instances, highlighting the transformative potential of BCI for enhancing the quality of life in speech-impaired individuals[146]. Guerreiro Fernandes *et al*.[149] addressed crucial aspects of implementing speech BCIs, noting optimal speech decoding performance in the ventral 50% of the sensorimotor cortex and advocating for the use of unilateral surface electrodes in this region. These insights are pivotal in directing future clinical practices to ameliorate the quality of life for those with language disorders. Another investigation into decoding speech-related neural activities through long-term implanted ECoG devices revealed that patients could reliably control external devices via BCI without the need for recalibration or retraining, thereby confirming the sustainable efficacy and stability of BCI applications[150].

Monitoring neurological activity during anesthesia

BCI technology demonstrates potential applications in individuals with intact neurological function, particularly in the context of monitoring neural activity during anesthesia administration.

Recent advances in BCI for intraoperative awareness detection

Recent research has demonstrated an innovative BCI system utilizing Median Nerve Stimulation (MNS) to detect intraoperative awareness during general anesthesia. A study involving 16 healthy participants investigated the effects of MNS on the motor cortex and its application in detecting motor intent during anesthesia[151]. The findings revealed that MNS induced specific modulations in the motor cortex, including Event-Related Desynchronization (ERD) during stimulation and Event-Related Synchronization (ERS) post-stimulation. These modulations were significantly affected when participants attempted Motor Imagery during MNS.

By comparing the classification accuracy of MI versus rest state and MI during MNS versus MNS alone, researchers found that the BCI system incorporating MNS demonstrated higher classification accuracy compared to traditional systems based on MI state versus rest state. This approach provides a foundation for developing new techniques to effectively detect intraoperative awareness during general anesthesia, potentially improving the monitoring of anesthesia depth and prevention of intraoperative awareness.

Another study conducted on 12 healthy volunteers tested the offline classification performance of a motor-based BCI under two different concentrations of propofol anesthesia[152]. The results indicated that even under the influence of propofol, the BCI could detect movement attempts with accuracies of up to 85 and 83%. Notably, the study demonstrated that classifiers trained in the awake state could detect movement attempts in the sedated state with above-chance accuracy, providing important evidence for the application of BCI technology across different states of consciousness.

While these results are promising, the researchers note that the relationship between motor responses and consciousness states, as well as their clinical relevance in intraoperative awareness, requires further investigation. Overall, they showcase the immense potential of BCI technology in anesthesia monitoring and intraoperative awareness detection, offering new possibilities for improving surgical safety and patient outcomes.

Prospects and future directions

Prospects

BCI technology holds substantial promise for diagnosing, treating, and rehabilitating various neurological conditions, but its clinical deployment is still predominantly experimental and beset by numerous technical, ethical, and practical hurdles. To tap fully into BCI's potential in health care, critical focus areas need further development:

Integration with emerging technologies

Integrating BCI with artificial intelligence, machine learning, and neural networks can considerably boost these systems' adaptability and efficiency. AI-enhanced BCIs can tailor personalized treatment plans by learning unique brain patterns, while AI and ML algorithms can process vast amounts of EEG data to detect subtle patterns that enhance BCI system responsiveness and precision. For instance, using deep learning to decode complex brain signals can lead to improved control and communication. Moreover, AI and ML can refine BCI performance continuously through real-time adjustments, ensuring consistent functionality across different conditions.

Biocompatibility and safety of long-term implants

It is vital to assess the effects and risks associated with long-term implants to biological tissues. Advances in materials science and bioengineering could enhance implant biocompatibility, and innovations in biomaterials might yield safer, more effective long-term implants. For example, using nanomaterials and biodegradable substances can minimize inflammatory responses and rejection rates, improving implant longevity and reliability. Furthermore, safety standards and evaluation methods are continually updated to guarantee the safety and efficacy of new materials in clinical settings.

Interdisciplinary collaboration

The advancement of BCI technology necessitates collaboration across various fields, such as neuroscience, biomedical engineering, computer science, neurosurgery, and clinical medicine. Enhanced cooperation between academia, industry, research institutions, and medical centers is essential for spurring innovation and clinical application. Such collaboration brings diverse ideas and technological innovations, with neuroscientists providing insights into brain functions, biomedical engineers developing efficient algorithms, neurosurgeons conducting precise surgeries, and clinicians offering insights into patient care and feedback.

Ethical and privacy protection

Addressing the ethical implications associated with privacy, security, and potential data misuse is crucial. Robust ethical guidelines and regulatory frameworks must be established to ensure BCI technology's responsible development and deployment. Protecting user data privacy and preventing misuse are increasingly critical as BCI technology advances. Ensuring strict encryption and access control for sensitive brain data is necessary to prevent unauthorized access and misuse. Furthermore, human–machine integration raises ethical questions about personal identity, autonomy, and accountability. Clear ethical frameworks and guidelines are essential to responsibly use technology and safeguard users' rights and dignity.

Future directions

Anticipating future advancements, the progressive integration and broader adoption of BCI technology are poised to catalyze notable advances in several key domains:

Bidirectional brain–computer interfaces

These interfaces facilitate reciprocal communication between the brain and external apparatuses, markedly refining the precision of control and enriching the user interaction within BCI systems. The process from 'brain to machine' decodes and translates EEG signals from the user into executable commands for controlling external devices, like robotic arms or digital interfaces. Conversely, the 'machine to brain' channel transmits sensory information, such as tactile or visual data, from external devices to the user's brain, incorporating feedback mechanisms. For instance, in prosthetic applications, bidirectional BCIs not only empower users to command the movements of prosthetics but also relay sensory feedback, allowing users to discern textures and temperatures of contacted objects, thus facilitating a more intuitive and adaptable operation.

International cooperation and standardization

The global collaborative efforts are crucial in advancing the standardization of BCI technologies, facilitating data interchange, and adopting best practices across borders. Such international alliances hasten technological advancement and the ubiquitous distribution of novel innovations. The formulation of global standards and agreements enables research entities and corporations worldwide to exchange data, technologies, and insights, which promotes a harmonized progression of BCI technology. Standardized data constructs and interface protocols bolster system compatibility and interoperability, curbing both developmental expenditure and duration. Moreover, international collaborations nurture technological innovation and the exchange of knowledge via joint research endeavors and scholarly interactions, thereby cultivating professional expertise globally.

High-performance brain–computer interfaces

Presently, the communication throughput and efficiency of BCIs remain limited. Essential to the realization of high-performance BCIs is the establishment of robust communication channels between the brain and external devices, necessitating substantial enhancements in signal transmission and processing to boost the speed of data handling and system responsiveness. The evolution of high-performance BCIs involves the integration of ultra-high-density electrode arrays for finer brain signal resolution, the implementation of potent signal-processing algorithms for real-time decoding of complex neural activities, and the employment of advanced computing resources for accelerated data analysis. Such developments are aimed at achieving quicker system responses and heightened control precision, thereby offering users a more seamless and instinctive interface experience.

Conclusion

BCI technology demonstrates immense potential in the diagnosis, treatment, and rehabilitation of neurological disorders, yet its clinical application remains largely experimental and faces numerous challenges. These challenges include enhancing the biocompatibility and long-term stability of materials while developing advanced electrode and sensor technologies; achieving system miniaturization and portability; optimizing signal processing algorithms for improved decoding accuracy and real-time performance; designing more intuitive user interfaces; verifying clinical efficacy; addressing ethical and privacy concerns; and strengthening interdisciplinary collaboration. Future research should focus on developing bidirectional and high-performance BCIs, creating long-term stable implantable electrodes, optimizing real-time signal-processing algorithms, and exploring closed-loop stimulation systems. Additionally, conducting large-scale clinical trials and establishing robust ethical guidelines and regulatory frameworks are essential. Advancing international cooperation and standardization will be crucial in facilitating these research efforts and their clinical translation. Despite these challenges, the future of BCI technology in the treatment of neurological disorders is promising. With technological advancements and strengthened interdisciplinary collaboration, BCIs are expected to offer revolutionary diagnostic and therapeutic solutions, significantly improving the quality of life for patients. Neurosurgery will play a crucial role in translating BCI research into clinical applications. However, it is imperative to approach the development of BCI technology with caution and responsibility, ensuring that patient benefits are prioritized and that ethical and societal norms are upheld. By addressing these challenges and advancing the aforementioned research directions, BCI technology is poised to achieve significant breakthroughs, offering new hope to patients with neurological disorders and driving the overall advancement of neurotechnology.

Ethical approval

Not applicable.

Consent

Not applicable.

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Author contribution

H.Z.: conceptualization, data curation, and writing – original draft; L.J. and X.J.: investigation and writing – original draft; S.Y. and H.L.: draw a picture and writing – original draft; J.F., S.Z., Q.X., and J.G.: validation and visualization; X.W. and B.W.: project administration, resources, supervision, and writing – review and editing. All authors finalized the manuscript, refined the article, contributed to the final manuscript, and approved it for publication.

Conflicts of interest disclosure

The authors declares no conflicts of interest.

Research registration unique identifying number (UIN)

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Data availability statement

The data that support the study findings are available upon reasonable request from the authors (Baojian Wei).

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