Chapter

Applications of Brain Computer Interface in Present Healthcare Setting

Zahrah Alwi Alkaff, Nurul Hashimah Ahamed Hassain Malim, Putra Sumari and Jafri Malin Abdullah

Abstract

Brain-computer interface (BCI) is an innovative method of integrating technology for healthcare. Utilizing BCI technology allows for direct communication and/or control between the brain and an external device, thereby displacing conventional neuromuscular pathways. The primary goal of BCI in healthcare is to repair or reinstate useful function to people who have impairments caused by neuromuscular disorders (e.g., stroke, amyotrophic lateral sclerosis, spinal cord injury, or cerebral palsy). BCI brings with it technical and usability flaws in addition to its benefits. We present an overview of BCI in this chapter, followed by its applications in the medical sector in diagnosis, rehabilitation, and assistive technology. We also discuss BCI's strengths and limitations, as well as its future direction.

Keywords: BCI, EEG, healthcare, clinical application, diagnosis, neurorehabilitation, assistive technology

1. Introduction

Technological advancement is ushering in a new frontier in the healthcare sector with the emergence of brain-computer interface (BCI). The BCI is a brain-machine interface that interacts with external parameters in real time, offering innovative solutions for various medical conditions and disabilities. In the recent decades, BCI has increasingly become a subject of great interest and importance, transforming the medical device industry with its vast potential applications [1]. It is the fastest-growing field in modern computing, with the study of BCI commonly aiming to support, enhance, or restore human cognitive or sensory-motor functions [2], particularly in cases where satisfactory treatment options are currently lacking.

BCI technology has transformed numerous fields of study, spanning domains such as healthcare, smart environments, neuromarketing and advertising, neuroergonomics, security, education, games, and entertainment. Many studies are underway around the world to investigate the potential of BCI applications as a viable piece of technology in the fields of healthcare and medical sciences, with particular emphasis on assisting individuals and improving their quality of life, especially those affected by diseases, disabilities, impairments, or paralysis. BCI systems play a crucial role in areas such as diagnosis, neurorehabilitation, and assistive technology, aiming to restore patients' ability to engage with and control different activities and environments, thereby compensating lost neurologic functions. These systems enable users to communicate, operate wheelchairs or prostheses, and support rehabilitation from a care perspective [1, 3, 4]. As such, BCIs may play a crucial role in managing, and possibly even treating, these conditions in the future [5].

BCIs offer numerous potential applications in clinical contexts, namely, the rehabilitation and restoration of lost neurological function [6]. In particular, the BCI feature offers hope to those who are suffering from the most severe motor disabilities, such as amyotrophic lateral sclerosis (ALS), spinal cord injury stroke, and other serious neuromuscular diseases or injuries. These technologies have the potential to significantly improve these patients' quality of life by enhancing their personal autonomy, independence, and mobility. Furthermore, BCIs serve as valuable tools for neurofeedback and neuroplasticity training, facilitating the recovery process in patients with neurological disorders such as stroke, Parkinson's disease, or traumatic brain injuries [7]. Beyond motor-related applications, BCIs have a broad range of clinical and nonclinical uses. In clinical contexts, they are employed for the treatment of mental health issues, offering novel avenues for diagnosing and treating psychiatric disorders like depression, anxiety, and post-traumatic stress disorder (PTSD), while in nonclinical domains, BCIs offer possibilities for neuro-enhancement, neuromarketing, and gaming products [3].

Despite the immense potential of BCIs, integrating contemporary technology into practical and useful clinical applications is always fraught with difficulties, and BCIs are no exception. However, as research and development in this field continue to advance, the future holds great promise for further breakthroughs that will transform the healthcare landscape, improving the lives of countless individuals worldwide. This chapter aims to provide an overview of BCIs with regard to its clinical application. We start by defining BCI and discussing the different types of BCIs and the essential components of a BCI system. We then explore the potential applications of BCI systems, as well as some of the limitations and challenges that the field faces. Finally, we look forward to the future developments that may shape the field in the coming years.

2. Overview of BCI

2.1 Definition

A BCI, sometimes referred to as brain-machine interface (BMI), is understood as a system that enables real-time communication and/or control between the human brain and external devices. Some of these external devices include wheelchairs, computers, robotic arms, and muscle-activating gadgets. It is important to note that voice-activated or muscle-activated communication system does not fall under the BCI category. Essentially, a BCI is designed to identify and analyze brain signals that represent an individual's intention and then converts those signals into real-time device commands that execute a task [8].

BCI enables users to interact with the environment by using brain signals rather than by relying on muscles and nerves. It substitutes nerves and muscles, as well as the movements they produce, with hardware and software that measures brain

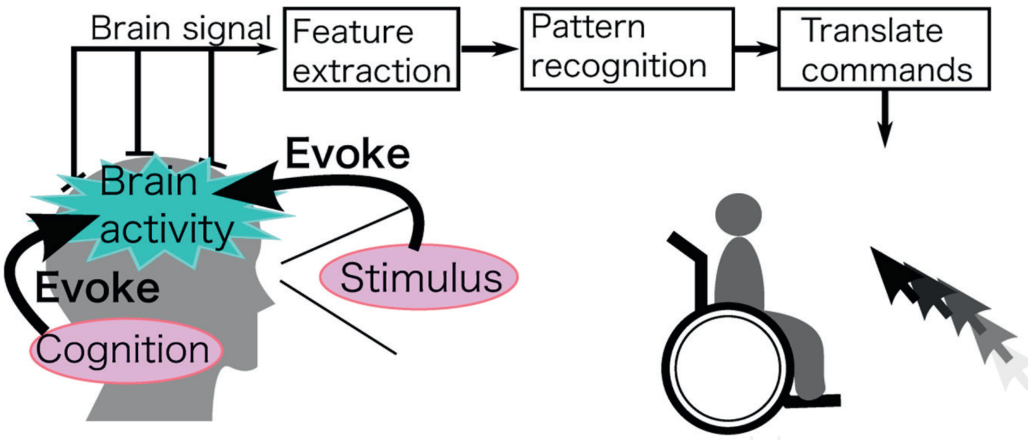

Figure 1.
Schematic representation of a basic BCI showcasing the origin of targeted brainwave signals from visual stimuli or cognitive processes, followed by their acquisition, processing, and translation into actionable commands [9].

signals, which are then translated into actions by transforming electrophysiological signals from mere reflections of central nervous system (CNS) activity into messages and commands to accomplish the user's intent [7, 9]. For a visual representation of the process by which targeted brainwave signals originate from visual stimuli or cognitive processes, **Figure 1** offers valuable insight [9]. The figure visually depicts the sequential steps of a BCI operation that will be further described in the following section.

Successful BCI operation relies on the essential interaction between the user and the BCI, both acting as adaptive controllers. To ensure seamless functionality, the user and the system must collaborate and synchronize, entailing a period of practice and mutual adaptation [7, 8]. Through this process, the user will be able to generate specific brain signals that encode intention, and subsequently, the BCI deciphers the signals and processes them into orders to another device to perform the user's desired action. The BCI functions as an adaptive close-loop control system to replace traditional neuromuscular output channel. Thus, the BCI presents the user with real-time feedback so that the user can augment the brain signals to optimize the intended action [10]. This dynamic partnership between the user and the BCI is instrumental in achieving optimal BCI performance and unlocking its full potential.

In theory, a wide range of neurobiological signals illustrating brain activities could be captured and applied to operate a BCI. These signals can be broadly classified into three types based on the biophysical environment of the signal source: electrophysiological, magnetic, and metabolic [11]. This chapter will focus on electrophysiological signals. Electrical signals generated by brain activity have been studied using two main approaches. The first method is concerned with detecting brain oscillations that are not always caused or correlated by external stimulation, whereas the second approach focuses on investigating the effects of various trigger inducing conditions on the oscillations, such as in evoked potentials [12, 13].

2.2 Components of BCI

An EEG machine can only record the brain signals and does not produce or process signals into the user's environment. BCIs are the computational systems that obtain the neural signals, analyze them, and decode the information into commands that can be conveyed to an output device to perform its designed function. A BCI system consists of various components that enable the acquisition, processing, and translation of neural

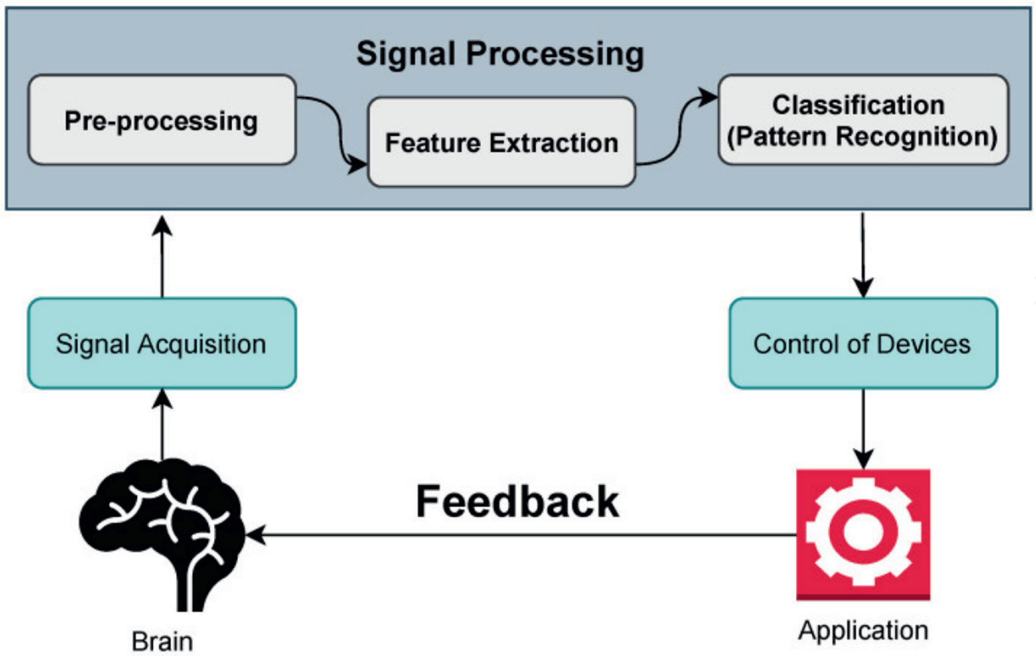

Figure 2.
Basic architecture of BCI system from Mridha et al., [4]. This diagram offers a clear and comprehensive illustration of the key components and their interconnections within a BCI system. It highlights the flow of information from the brain to external devices, emphasizing the crucial stages of signal acquisition, processing, decoding, device output, and the presence of a feedback loop.

signals into device commands. The BCI system's interactive functionality is characterized by the operating protocol, which needs to be flexible and serve the specific need of the user. The system is made up of four steps: (a) signal acquisition, (b) feature extraction, (c) feature translation, and (d) device output. These components work together in a sequential manner to facilitate effective interaction between the user and the BCI system. In this section, we provide an overview of the key components involved in a BCI system. The information below is extracted from the literature [1, 8, 10, 14]. Please refer to **Figure 2** for a depiction of the basic architecture of a BCI system.

2.2.1 Signal acquisition

A vital component of any BCI-based system is the capability to record brain generated oscillations. Signal acquisition is the measuring of the brain's neurophysiologic condition using a specific neuroimaging sensor modality. It displays the volitional neural actions produced by the user's present activity. The recording interface monitors neural information depicting one's objective embedded in present brain activity during BCI operation. The electrodes collect, amplify to levels suitable for electronic processing, and digitize the electrical signals from the brain. The appropriate signal acquisition method and its measured phenomena are determined by the BCI application and the classification of its intended users.

2.2.2 Feature extraction

In the feature extraction stage, relevant signal features encoding user intent are extracted from the acquired brain signals. These features can be derived from the frequency-domain, time-domain, or a combination of both. The amplitudes or latencies of event-evoked potentials, frequency power spectra, or firing rates of particular cortical neurons are the most regular signal characteristics used in modern BCI systems. Strong correlations between the extracted electrophysiological features and the user's intention are vital for successful BCI functioning. The features that will be used to control the BCI are extracted from the digitized data using filtering technique. For reliable evaluation of the brain signal characteristics, environmental and physiological artifacts, such as electromyographic signals, are avoided or eliminated.

2.2.3 Feature translation

The feature translation process involves converting the extracted and processed signal features into appropriate device commands. This stage requires mapping the brain's electrophysiological attributes or parameters to control parameters that govern specific actions, such as cursor movement on a computer screen, letter selection, prosthetic control, or the operation of other assistive devices. The range of available individual signal characteristics from the user must encompass the entire spectrum of device control; hence, a translation process must be dynamic to accommodate and react to the signal features' ongoing changes.

2.2.4 Device output

The final component of a BCI system is the device output, which utilizes the extracted and processed signal features to operate external devices. The user receives feedback from the device operation, closing the control loop. Common applications of device output include moving a cursor on a computer screen, controlling a wheelchair or other assistive devices, operating a robotic arm, or enabling movement of a paralyzed limb through the use of a neuroprosthesis. Currently, the computer screen is the most commonly applied output device for communication purposes.

2.3 Types of BCI (noninvasive and invasive)

Providing a new output channel, BCI technology revolutionizes human-computer interaction by harnessing brain signals to communicate and control external devices, circumventing the conventional neuromuscular and peripheral nerves pathways. These devices allow individuals to interact with computers while measuring their brain activity, enabling the BCI to discern the user's intent by interpreting brain signals, and issuing corresponding commands for desired actuation [10]. These devices typically rely on the interpretation of electrophysiological brain signals, commonly captured using techniques such as electroencephalography (EEG), electrocorticography (ECoG), and near-infrared spectroscopy (NIRS) [15, 16]. Among these techniques, EEG is the most widely practiced for BCI applications [16–18].

Electrophysiological signals can be observed on the surface of the scalp, under the scalp, or even within the brain itself. Some systems use magnetic sensors or other methods to collect other physiological signals. Based on the degree of invasiveness of the techniques used, BCI systems can be classified into two main categories: invasive and noninvasive methods.

Invasive BCI techniques require neurosurgery to implant electrodes directly into the brain tissue, rendering it a highly complex, expensive, and dangerous procedure. As a result, invasive BCIs are primarily reserved for patients who are blind or immobilized [4]. To address these challenges and expand the accessibility of BCI technology, noninvasive BCI approaches have gained significant attention. The noninvasive method rely on external sensors, such as scalp electrodes or wearable devices, to capture brain signals. Hence, in recent years, research interest has been lying in developing noninvasive wireless devices that address these concerns. Currently, due to practical constraints and limitations associated with invasive BCI, its clinical applications have relied mainly on scalp-recorded EEG signals to date. Overall, each method—whether invasive or noninvasive—has its pros and cons; therefore, the choice of BCI approach may be determined by the individual's specific BCI usage requirements and overall goals.

2.3.1 Noninvasive

The noninvasive method is the preferred and the safest of these options [19]. A noninvasive BCI operates on the principles of EEG and does not require any surgical or intrusive intervention as signals are recorded from the scalp [3]. The noninvasive BCI is the present focus of the majority of studies, which is expected to grow significantly in the coming years. Although it contains less data than intracortical recordings, EEG recorded by scalp electrodes has similarly been shown to be a viable basis for BCI control [20]. The noninvasive BCI offers various benefits over the invasive BCI owing to its simplicity, minimal risk, lower costs, ease of use and operation, portability, and high temporal resolution [2]. No surgical intervention is required, and thus, there is no possibility of scar tissue or tissue damage of the brain, making it a much safer approach. Noninvasive BCI can be used by people from all walks of life, and it does not require the supervision of medical professionals. However, due to the interference of the skull, this process has a poorer spatial resolution, captures weaker signals, and has limited frequency range [14]. Moreover, it is more prone to outside noise and artifacts from electromyographic (EMG) or electrooculographic (EOG) activity.

EEG signals are used to control many devices such as wheelchairs. Kaufmann et al. proposed a BCI method for controlling a wheelchair using the EEG signals and tactile event-related potential (ERP), focusing on people with neurodegenerative diseases [21]. Fifteen participants were tested as they operated a virtual wheelchair around a building. The majority of participants established tactile ERP-BCI control that was reliable and accurate enough to control a wheelchair [21]. Following that, utilizing EEG and tactile ERP as well, Herweg et al. demonstrated to 10 healthy elderly participants how to teach the user to operate the wheelchair. The system uses 14 orders in virtual environments, achieving a 90% accuracy in the navigation tasks involving virtual wheelchair control [22]. More recently, it has been emerging as a promising approach in rehabilitation and assistive devices. In stroke patients, Li et al. examined a BCI-operated lower limb rehabilitation robot, which led to enhanced leg functional recovery that may arise in people who suffered stroke, and it also improved daily living activities [23]. Bundy et al. tested a powered exoskeleton operated by BCI using the spectral power from EEG data from undamaged cortical regions with 10 chronic hemiparetic stroke survivors that have moderate to severe upper-limb motor disability. Results demonstrated significant improvement in motor recovery [24]. Moreover, findings from Frolov et al. also revealed that incorporating exoskeleton-assisted physical therapy with BCI control can optimize poststroke recovery results [25]. Similarly, 13 study participants were able to use their brain activity to control a robotic arm and perform reach-and-grasp tasks with high accuracy using EEG-based BCI, exhibiting the practicability of prosthetics limbs operated by humans using noninvasive BCI technology [26].

2.3.2 Invasive

In invasive BCI, some form of brain surgery is required as the electrodes need to be attached on the human brain using techniques such as electrocorticography (ECoG), intracranial electroencephalography (iEEG), or deep brain stimulation (DBS). Each technique has its unique characteristics and applications.

ECoG is commonly used in clinical settings to identify brain areas that may be affected by surgical resection of lesions. ECoG signals are recorded from electrodes surgically positioned under the scalp and is considered partially invasive. The electrodes implanted track electrical activity emanating from the brain's cortical surface and provide accurate readings of neural activity, similar to EEG [1]. One of the key advantages of ECoG is its close proximity to the brain, as the removal of the insulating aspects of the skull and dura produces greater signal amplitude, resulting in superior temporal and spatial resolution and wider spectral bandwidth. ECoG enables the detection of higher-frequency (40-Hz gamma band) activity up to 200 Hz and beyond, along with lower-frequency (40 Hz) activity that dominates the EEG [14]. This enhanced signal quality makes ECoG an ideal tool for recording wider detectable frequency range and achieving better topographical resolution.

However, despite its advantages, this technique comes with a number of flaws, foremost being usability issues due to the involvement of a surgical procedure. While ECoG electrode arrays can be removed, this process necessitates the involvement of a skilled neurosurgeon. In addition to concerns regarding implant stability and infection prevention, medical complications can occur if the body fails to adapt to the insertion of a foreign object. Furthermore, ECoG-based systems face limitations in terms of the system's readout due to the relatively small size of the recorded brain area. Once the electrodes are affixed, they cannot be easily repositioned to monitor brain activity in different regions unless a surgical procedure is undertaken. As a result, the use of invasive recording in the real world has predominantly been limited to BCI-based medical applications catering to a select group of severely disable users such as neural motor prostheses device using BCI ECoG for paralyzed patients [6].

Vansteensel et al. fully implanted BCI that included a transmitter inserted beneath the skin on the left side of the thorax and subdural electrodes placed over the motor cortex in locked-in ALS patients. Using software that automatically extracted electrocortical signal features, the patient operated a software that has the ability to type, although somewhat slowly, by trying to move her hand [27]. Another study by Degenhart et al. implanted high-density ECoG electrode grids over sensorimotor cortical areas on two subjects with upper-limb paralysis due to ALS and brachial plexus injury. After training, participants were able to produce strong cortical modulation that could be distinguished between attempts to move their paralyzed limbs' hands and arms. Utilizing the somatotopic control method, they were able to deliberately modulate the control of the movement of a computer cursor with up to three degrees of freedom [28]. Subsequently, Cajigas et al. implanted a portable BCI on a patient with spinal cord injury with complete cervical quadriplegia to restore hand function. The BCI was made up of subdural surface electrodes that are embedded over the motor cortex of the dominant hand and is connected to an electric transmitter inserted below the clavicle subcutaneously to enable continuous readout of the electrocorticographic activity. During the preliminary 29-week laboratory trial, functional electrical stimulation of the dominant hand was triggered by movement-intent and, later, during at-home usage of a mechanical hand orthosis. Movement-intent date could be reliably deciphered, whereas various upper extremity tasks, such as lifting tiny items and transporting objects to particular targets, were performed better in both speed and accuracy [29]. Thus, an implanted BCI can be employed securely to robustly interpret movement-intent from the motor cortex, enabling precise volitional control of hand grasp.

ECoG is primarily employed for clinical purposes in humans due to its invasive nature and its application within a specific patient population. Consequently, one of the major challenges faced by BCI researchers in the field of ECoG is the scarcity of research subjects, as their availability is contingent upon the diagnostic and therapeutic conditions of patients. The invasive nature of ECoG and its clinical focus restrict the pool of potential participants for research studies. Additionally, the placement of ECoG electrode arrays is primarily guided by clinical considerations and the specific needs of patients, which may not always cover cortical areas associated with advantageous brain patterns for BCI applications.

Next, one of the most invasive technique employs intracortical acquisition, where electrodes are implanted under the cortex surface of the brain measuring spikes of action potentials in individual neurons or local field potentials. The ability to record activities of individual neurons with great signal quality makes this technique highly advantageous. This technique is utilized to aim for deeper brain regions such as the limbic system [30]. Electrodes are positioned in close proximity to signal sources; the arrays must be stable over time. The application of iEEG in source localization issues is highly urged because of its comparatively high spatial resolution. Similar to ECoG, iEEG are less affected by EOG and EMG activity and provide greater temporal and spatial resolution, higher bandwidth of up to 500 Hz [10]. However, other than complications of implantation surgery, the recording quality diminishes over time [31]. Long-term signal fluctuation could be observed during intracortical recording as a result of displacement of electrodes, increased tissue resistance, or neuronal cell loss. Additionally, if the system uses a stimulus to trigger a paralyzed limb, this extra input could have a sizeable noise impact [4].

The **Figure 3** presents an overview of a typical BCI system, providing a visual representation of the essential components and processes involved, as discussed in the previous paragraphs.

Finally, DBS, on the other hand, entails the implantation of electrodes deep within specific brain regions associated with neurological disorders and delivers electrical impulses through the implanted electrodes to modulate and restore balanced neural activity [32, 33]. It is a prominent application of BCI technology within the present healthcare setting as ongoing research is exploring the integration of these two approaches. BCI DBS enables real-time monitoring and analysis of brain signals, allowing for precise control and customization of stimulation parameters to optimize therapeutic outcome [32, 34]. These signals are then translated into commands that control the timing, intensity, and duration of electrical stimulation, enabling precise modulation of neural circuits involved in the pathogenesis of the disorder. The ability to customize stimulation parameters according to individual patient needs is a key advantage of BCI-based DBS.

Furthermore, it has shown significant efficacy in managing conditions like Parkinson's disease, essential tremor, dystonia, and certain psychiatric disorders [15, 34–36]. By targeting the dysfunctional brain circuits responsible for movement disorders, such as tremors and rigidity in Parkinson's disease, DBS can significantly reduce these symptoms and restore motor function [37–40]. Moreover, DBS has shown promising results in addressing treatment-resistant psychiatric conditions, such as obsessive-compulsive disorder, borderline personality disorder, and major depression, by

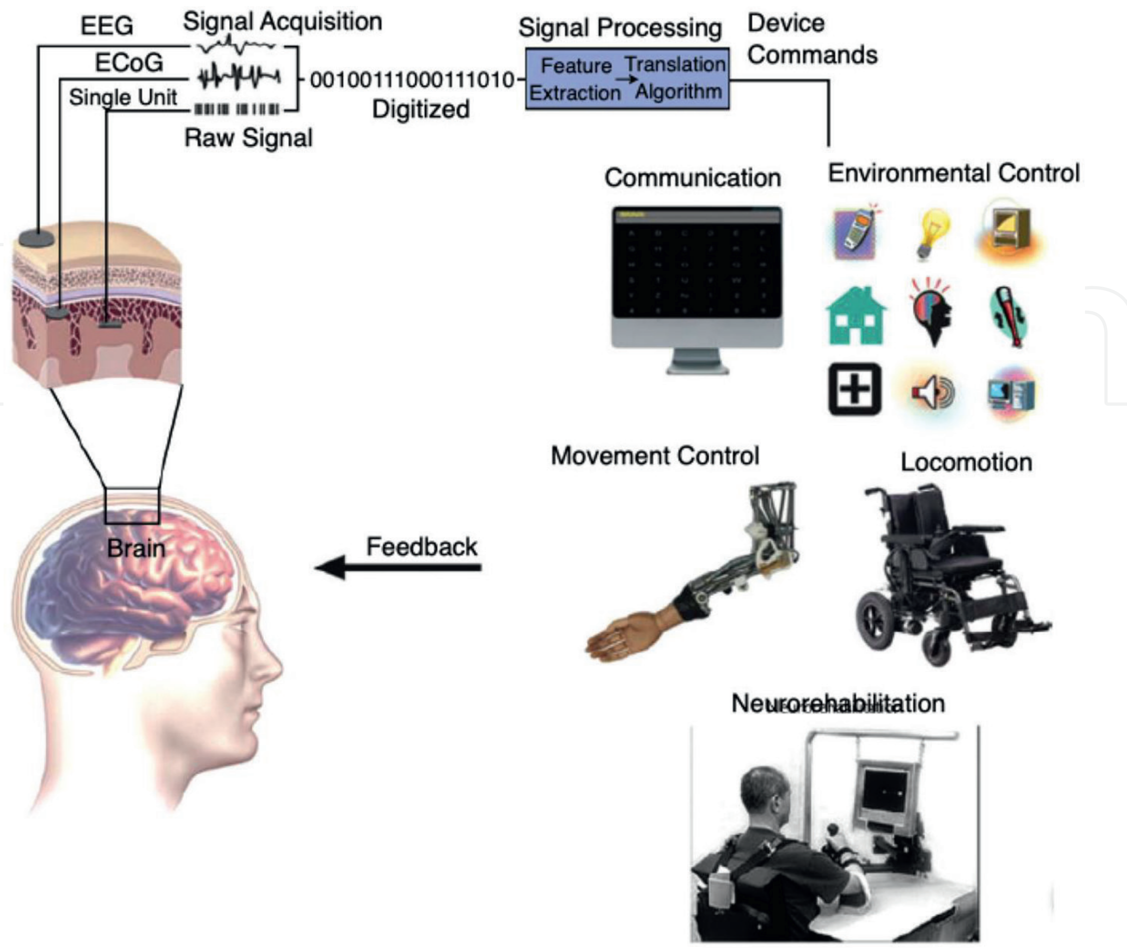

Figure 3.
Schematic overview of BCI [15]. The brain generates electrical signals that are captured using EEG, ECoG, or iEEG methods. These signals are processed using signal processing algorithms, and the resulting decoded commands are utilized to control a range of external devices for communication, environmental control, movement assistance, locomotion, and neurorehabilitation.

modulating the brain regions involved in emotional and cognitive processes [32, 34, 41]. Through the interface with the brain's electrical signals, BCI-based DBS allows for precise and targeted stimulation, leading to substantial improvements in motor function, reduction in tremors, and alleviation of symptoms [37, 42–45]. This innovative approach enhances the quality of life for patients who have previously experienced limited success with traditional therapies, opening new possibilities for neurologists and patients alike. However, much like ECoG and iEEG, DBS offers significant therapeutic benefits but carries surgical risks, and the long-term efficacy may be influenced by factors like electrode displacement or tissue response. While DBS has demonstrated efficacy in managing various neurological conditions and is a promising treatment option, it is important to note that findings in the field are limited and not without mixed results [32, 46–48], paired with significant methodological and ethical constraints within the two respective fields [49, 50]. Research in the field of DBS-BCI integration is ongoing, and further studies are needed to fully understand its effectiveness, long-term outcomes, and the factors influencing its therapeutic success. The complex interplay of brain circuits and individual variability contribute to the challenges associated with DBS-BCI, warranting continued investigation and refinement of this integrated approach.

In summary, ECoG, iEEG, and DBS are distinct invasive BCI techniques that require brain surgery for electrode placement. ECoG provides wide spectral bandwidth and good topographical resolution, while iEEG offers highly localized and precise recordings of neural activity. DBS utilizes electrical stimulation to modulate targeted brain circuits. While they offer distinct advantages in terms of signal quality and targeted stimulation, they also come with challenges such as surgical risks, limited repositioning capabilities, and potential long-term complications. Thus, ongoing research is needed focusing on improving electrode design, developing closed-loop systems that adapt stimulation parameters based on real-time feedback, and refining the surgical techniques involved. Each technique has its advantages and limitations, and the integration of BCI technology enhances their potential in managing neurological and neuropsychiatric disorders.

3. BCI clinical applications

This section offers a comprehensive exploration of the clinical applications of BCI technology. BCIs have shown tremendous potential in transforming healthcare and medical sciences by introducing groundbreaking solutions for diagnosis, rehabilitation, and assistive devices. Through an in-depth review of the existing literature, this section critically examines the body of research that focuses on BCI applications in clinical settings. Specifically, it highlights the significant contributions and advancements made in the domains of diagnosis and detection, rehabilitation, and assistive devices. To provide a concise overview of BCI applications in clinical contexts, **Table 1** presents a summary of key findings. By elucidating the current state of BCI clinical applications, this section aims to contribute to a deeper understanding of the implications and future prospects of this pioneering technology in the field of healthcare.

3.1 Diagnosis and detection

For starters, in diagnosis, BCI has helped predict and detect health issues such as abnormal brain structure in brain tumor and epilepsy with the mental state monitoring function of BCI systems [74]. An automated EEG analysis combines neural network techniques and digital signal processing and will be able to identify the presence of any abnormality or disease, eliminating the arduousness and chance error of manual analysis of EEG reading. A system developed by Sharanreddy and Kulkarni can identify EEG anomalies connected to seizures and brain malignancies. Using a feed-forward neural network, they are able to recognize the EEG signal as normal with a classification accuracy of 98%, brain tumor for 87%, and epileptic for 93% [51]. Many different methods have been explored for feature extraction and classification in the detection of epilepsy and brain tumor. Some of the most commonly used feature extraction methods in epilepsy detection tasks are frequency and time domain, with more recent studies employing discrete wavelet transform [52, 53] and convolutional neural network [54, 55]. Slow waves in EEG may be denoted to loss of local electrical activity due to the growth of a tumor on the brain, making it a useful tool for screening of suspicious causes. Particularly, EEG is better suited for detecting and diagnosis tumors on the cerebral hemispheres, as opposed to ones in the deeper subcortical regions that are harder to locate. Though limited, several studies have explored various methods for extraction and classification to provide accurate reliable detection of brain tumors some of which are independent component analysis [56], principal component analysis, and radial basis function [57]. As for disorders of consciousness, Spataro et al. tested a P300 BCI paradigm with a behavioral assessment

Application	Sample	Type/Signal	Reference
Diagnosis	Seizure and brain malignancies	EEG – feedforward neural network	[51]
	Epilepsy	EEG – discrete wavelet transforms	[52]
	Epilepsy	EEG – discrete wavelet transforms	[53]
	Epilepsy	EEG - convolutional neural network	[54]
	Epilepsy	EEG - convolutional neural network	[55]
	Brain Tumor	EEG – independent component analysis	[56]
	Brain Tumor	EEG – principal component analysis and radial basis function	[57]
	Disorders of Consciousness	P300	[58]
	Dementia	P300	[59]
	Sleep apnea	EEG-based deep learning neural net	[60]
Rehabilitation	Stroke	BCI with FES	[61]
	Stroke	BCI with FES	[62]
	Stroke	BCI with transcranial magnetic closed-loop stimulation	[63]
	Stroke and healthy subjects	BCI with peripheral electrical stimulation	[64]
Assistive Devices (Neuroprosthetic)	Seizure - prosthetic finger	ECoG-based BCIs	[65]
	4 participants - Robotic prosthetic arm	EEG based motor imagery BCI	[66]
	1 amputee subject - lower extremity prosthetic	EEG BCI	[67]
Assistive Devices (Environmental control)	12 healthy subjects and 2 disabled subjects	EEG BCI Smart home	[68]
	NA	EEG - Intention recognition	[69]
	3 subjects	Wheelchair control BCI with autonomous navigation technique • Motor imagery and P300	[70]
Assistive Devices (Communication)	3 paralyzed patients	High-performance iBCI • Assistive Communication device	[71]
	3 paralyzed patients	High-performance iBCI • Tablet Computer Control	[72]
	Person with paralysis and anarthria	High density ECoG • With natural language modeling	[73]

Table 1.
Overview of articles for BCI clinical applications comprising three main domains; diagnosis and detection; rehabilitation; assistive devices.

(Coma Recovery Scale- Revised) and reported its reliability and efficacy in improving diagnostic precision for the evaluation of consciousness level [58]. Other conditions that can apply BCI for diagnosis and classification are stroke diseases [75], dementia [59], and sleep apnea [60].

3.2 Rehabilitation

BCI systems may be used therapeutically to assist people in relearning and regaining effective motor function after impairing their neuromuscular function due to trauma or disease. Mobility rehabilitation is a type of physical therapy that can help people with mobility problems regain their abilities or regain function to a level or assimilate to their new disability [76]. Essentially, the BCI systems work by synchronizing brain activity that pertain and correlate to movement intent with real motions and sensations produced by end-effector devices, generating brain plasticity, and helping to restore normal central nervous system function [6]. BCI-based neurorehabilitation facilitates functional recovery and may improve quality of life. Primarily, SMR-based BCI systems are studied in movement control along with cortical stimulation.

In stroke rehabilitation, BCI is implemented to transform brain signals into desired movement of the paralyzed limb. Testing BCI with functional electrical simulation (FES), Biasiucci et al. reported that the intervention generated significant increase in functional connectivity between motor areas in the afflicted hemisphere, which was associated to functional improvement in chronic stroke survivors. This result was found more effectively than sham FES [61]. Moreover, Tabernig et al. also conducted a similar study and reported significant improvement posttreatment, suggesting that functional electrical stimulation commanded by BCI may be an effective neurorehabilitation for stroke patients [62]. Another study by Kraus et al. explores the utility of closed-looped cortical stimulation that is dependent on brain state sensorimotor desynchronization. The study produced significant increase in corticospinal excitability in healthy subjects, denoting that this approach may be applied in neurorehabilitation to activate brain plasticity and maximize motor recovery [63], as was also reported in Kim et al., in healthy subjects and stroke patients [64].

3.3 Assistive devices

Assistive technology (AT) helps individuals with motor, sensory, or cognitive disabilities in carrying out tasks that would be challenging or unattainable for them otherwise. Mobility aids, such as neuroprosthetic limbs, are one of BCI's primary applications in healthcare. This system helps those who are severely incapacitated due to illnesses like persistent peripheral neuropathies, ALS, cerebral palsy, spinal cord injuries, brainstem stroke, or muscle dystrophies [6]. According to Mak and Wolpaw, the major user demographic for current BCI systems is made up of patients who still have minimal neuromuscular control, such as weak eye movements or a small muscle twitch, as traditional assistive communication technology that relies on muscle movement is insufficient and unsuitable for them [10]. Thus, BCI systems will allow them more efficient and reliable control and communication with the environment.

For those who are paralyzed, regaining independent locomotion is another crucial concern. Several studies recommended that patients who struggled or are unable to regain upper limb movement would benefit from using neuroprosthetic devices that use motor imagery-based BCI to recover normal functioning [77].

Hotson et al. showed the use of ECoG-based BCIs in a human subject on the populations of sensorimotor cortex's native functional anatomy to control and move individual prosthetic finger in real time [65]. Bousseta et al. also devised a novel technology using mental imagery and cognitive tasks to control the movement of a robotic prosthetic arm that can move in up, down, left, and right directions. The system had an average accuracy of 85.45% across four participants [66]. A case study by Murphy et al. was also successful in demonstrating the viability of employing EEG-BCI to control a lower extremity prosthetic. The transfemoral amputee participant was trained with EEG rhythm-feedback to move a prosthetic knee and unlock the knee by switch activation [67].

Other than movement control, BCI-based environmental control would also greatly contribute to the well-being and daily living of people with severe disabilities and provide relief for caregivers. This will enable users to operate domestic appliances including door openers, lights and bulbs, mechanized beds, TVs and stereo systems, and telephones from a distance with the integration of EEG-based BCI technology [10]. Kosmyna et al. devised a BCI control mechanism for smart homes that permits users to control a coffee machine, lighting, shutters, and a TV set. They discovered that 12 healthy subjects achieve 77% task accuracy, whereas two disabled subjects achieve 81% accuracy [68]. However, Minguillon et al. reviewed the feasibility of EEG-BCI for potential daily applications and denoted that existing artifact removal techniques require further development before they can be used in real-world EEG-BCI [78]. Other studies are also exploring its utility and proposing different approaches and mechanisms such as Yue et al., to improve intention recognition accuracy [69]. To resolve the issue of mental burden as well as unstable and noisy EEG signals, Zhang et al. integrated BCI with an autonomous navigation technique for wheelchair control. The researchers tested both BCI based on motor imagery (MI) or P300 and found them to be effective [70]. This works by allowing the user to choose a destination using a MI or P300, and the automatic navigation system determines the path and waypoints.

On top of that, another application for BCI within this context is communication. Pandarinath et al. showcased how BCIs can be useful as powerful assistive communication devices for people who have reduced motor function. Three paralyzed participants tested a high-performance intracortical BCI (iBCI) for communication, producing a good typing rate and information throughout [71]. In a study by Nuyujukian et al., three paralyzed subjects were able to control a tablet computer through iBCI with multielectrode array attached to the motor cortex [72]. A step forward from the current assisted communication technique is a program that interprets words and sentences from patients' cerebral cortical activity directly. Recently, Moses et al. showed that complete words and phrases could be deciphered from electrical activity in the sensorimotor cortex of a person with paralysis and anarthria who was trying in vain to make understandable speech. Decoding was accomplished at 15 words per minute with a 25% error rate when paired with natural language modeling that predicts likely future words [73].

4. Limitations and strengths

BCI has made a lot of progress in the past 20 years. The strength of BCI lies in its potentiality and utility. The notion of controlling an external device with one's thoughts is a very favorable and viable respite for people with impaired functions such as speech or movement. Within the healthcare paradigm, developments in BCI system endeavor to provide a specialized multimodal approach to communication and therapeutic intervention. BCI technology is valuable and useful because it provides an opportunity for those who cannot move or speak to communicate and engage with others as well as operate appliances and assistive devices such as computers, home appliances, and speech synthesizers [79]. Beyond its promising applications and integration into the lives of people with motor impairment, BCI benefits by bridging its scientific understanding and experimental design into clinical benefits, facilitating real-time communication between the user and the outside world.

No BCI system and technique developed are currently free from limitations. Different approaches and types present their respective advantages and drawbacks. A satisfactory solution has not yet been found for the safety and long-term stability of the electrodes applied in invasive BCI systems. The electrodes are usually implanted temporarily and are limited to short-term studies. Recently, Benabid et al. had implanted a participant with tetraplegia with two bilateral wireless epidurals with 64 electrodes to control a four-limb neuroprosthetic exoskeleton that was found to be stable over a period of 24 months [80]. Additionally, the electrodes in invasive BCI can be implanted only in a limited range of sites and can record only few cell populations, of which the recording quality declines over time [31]. However, the use of microelectrode arrays has evolved and attained popularity as a means of real-time capture of the current local neural activity state. In both preclinical and even clinical trials, recent improvements in array design and fabrication have enabled the development of multichannel probes that are perfectly matched to the geometry of the selected area of the brain [81, 82].

On the other hand, EEG-based BCI systems, which are noninvasive and do not need for surgery or the ongoing upkeep of implanted electrodes, do not have these hazards or concerns because the electrodes are surface and simple to replace. However, EEG-based devices can only detect relatively weak and limited frequency brain waves. Albeit so, within the recording modalities, EEG-based BCIs are the most affordable and have now been used for clinical applications.

Usability challenges relate to human acceptance and constraints. First and foremost is the heterogeneity of the human brain. Neurological issues encompass a wide range of problems that relate to the anatomy and structure of the brain. These problems can be due to the complexity of our genetic makeup, or the diversity of the structure of human brains [14]. The psychological factors of memory load, fatigue, attention, conflicting cognitive processes, and the individual qualities of the user, such as lifestyle, gender, and age, all directly and immediately affect the brain dynamics [4]. For the BCI to function effectively, training is required for the user to give them the necessary skills to communicate with the system and learn how to control their neurophysiological signals. However, this process is time-consuming and laborious as proper guidance and repeated sessions are needed for the user. Determining the appropriate number of training sessions required may ease the process for both parties, avoid fatigue, and produce positive outcomes and consistent performance [83]. In the initial phase, the user is shown and taught how to operate the system and control brain feedback signals. Subsequently, during the calibration phase, the signal from trained users is applied to train the classifier [14].

BCI systems may be complicated and challenging for users to manage though designing a user-friendly simple interface is effortful for researchers [84]. The ability to translate current technology into real-life practices is imperative to allow for widespread usage of BCI. It requires signal acquisition equipment that is affordable, transportable, robust, commercially viable, and simple to operate. Apart from weariness from wearing electrodes, users experience fatigue as they have to maintain intense concentration and mental effort to produce input to the BCI. The discomfort from the heavy EEG headset also affects the user experience.

In real-life, day-to-day setting, the BCI application may be limited due to the presence of artifacts and lack of mobility given to users. Home BCI systems ought to function consistently in dynamic and irregular settings that ordinarily contain electronic noise sources. Even the use of implantable neural bypass systems is currently restricted to lab settings since patients must be constantly linked to an external power supply and recording equipment [85, 86]. Though there are studies conducted using EEG-BCI in home environment instead of in laboratory settings, many technical issues still need to be resolved before it can be widely utilized [1]. This is due to its poor signal-to-noise ratios (SNR), susceptibility to artifacts, and role of caregivers in maintaining and operating it, which makes it difficult to utilize it conveniently at home. Potential BCI users' physical and social situations, such as their living arrangements, social networks, and support systems, are crucial. Home BCI systems must be smaller than those used in laboratories and able to blend in with the user's surroundings with little to no disruption.

Technological issues are problems associated with various components of the BCI system. The recorded electrophysiological properties of brain activities provide challenges due to nonlinearity, noise, non-stationarity, the dimensionality curse, and limited training sets [4]. ERPs are target-specific and are created by external stimulation. Patients with disabilities may not be able to successfully use BCI systems that are visual-based or auditory-based if they are visually or hearing impaired. This may lead to high variability and poor performance in the patients. BCIs systems should be customized to users' suitability and capacities.

5. Future direction

BCI will continue to develop and advance as research continue into the development of diagnostic measures, treatment, and assistive technology. Although BCIs have shown promise for implementation in therapeutic environments, including patients' homes, their application is still limited to research settings. BCI technologies have been proven to be reliable and effective. Despite so, most of the recently published research are essentially proof-of-concept experiments that lack any data from clinical trials demonstrating regular and routine use by patients. It can even be said that only until this technology reaches the consistency of natural muscle activity will it be acceptable by the general population for everyday use. Therefore, depending on the size, complexity, and effectual running of the EEG device, research should account for the acceptance and practicality BCI systems when designing and developing [12]. Furthermore, the potential for BCI applications could be significantly increased if noninvasive BCI systems with various independent control channels such as multidimensional control of neuroprosthesis [10] or hybrid signals [8, 19, 87] are developed further. This would allow for users to execute more challenging tasks, such as the performing sequential movements or seamlessly ceasing the execution once completed.

Additionally, adoption of BCIs in healthcare systems necessitates the involvement of various stakeholders as well as an understanding of their perspectives and roles. This will steer the advancement of BCI and foster confidence and support in its application. The collaborative efforts of scientific researchers, healthcare personnel, and the tech industries will pave the way for commercialization and make BCI accessible to the public.

6. Conclusions

To sum up, the BCI technology exhibits significant potential to revolutionize the healthcare industry by enabling direct communication and control between the brain and external devices. The chapter at hand has highlighted the various applications of BCI technology in the healthcare domain, encompassing diagnostic, rehabilitative, and assistive technology purposes. Although BCI technology holds potential for addressing neuromuscular disorders, it presents technical and usability obstacles that necessitate additional investigation. The benefits of BCI technology in healthcare are apparent and indisputable, though, and continuous research will surely yield novel applications and greater outcomes. Hence, the technology of BCI exhibits immense potential for the healthcare sector, and it is anticipated to have a substantial impact on ameliorating and augmenting the standard of living of individuals who suffer from functional disabilities.

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Conflict of interest

The authors declare no conflict of interest.

Author details

Zahrah Alwi Alkaff[1], Nurul Hashimah Ahamed Hassain Malim[2]*, Putra Sumari[2] and Jafri Malin Abdullah[3,4,5]

1 School of Medical Sciences, Universiti Sains, Malaysia

2 School of Computer Sciences, Universiti Sains Malaysia

3 Department of Neurosciences, School of Medical Sciences, Universiti Sains Malaysia Health Campus, Kota Bharu, Malaysia

4 Brain and Behaviour Cluster, School of Medical Sciences, Universiti Sains Malaysia Health Campus, Kota Bharu, Malaysia

5 Department of Neurosciences and Brain Behaviour Cluster, Hospital Universiti Sains Malaysia, Universiti Sains Malaysia, Health Campus, Kota Bharu, Malaysia

*Address all correspondence to: nurulhashimah@usm.my

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