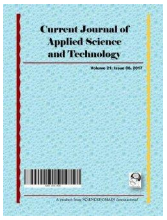

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Prospects and Problems of Brain Computer Interface in Healthcare

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Authors' contributions

This work was carried out in collaboration between all authors. Author IO designed the study and wrote the first draft of the manuscript. Authors IR and OO managed the analyses of the study. Authors IG and OJ managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Brain-Computer Interface (BCI) otherwise known as a Brain-Machine Interface (BMI) is an emergent technology whose goal is to create a real-time and direct communication pathway between the brain and external devices such as computers, robots, artificial limbs and wheelchairs. In BCI, cerebral or brain activities control these devices by transmitting and receiving signals from the brain. BCI is applied in healthcare to improve the communication capabilities of people living with disabilities or locked in syndrome such as traumatic brain disorders, Amyotrophic Lateral Sclerosis (ALS), spinal cord injury, brain stem stroke and other severe motor disabilities. BCI also increases the independence of disabled individuals by improving their muscle control. Consequently, BCI improves the quality of life of disabled persons by allowing this group of people to live a normal and comfortable life. In spite of the benefits of BCI, the technology is not widely deployed in healthcare. This is because of the numerous challenges associated with it. One of the basic limitations of BCI is that the signals received from the brain are prone to interference. Furthermore, legal and ethical concerns such as the risk of infection or hemorrhage, psychological

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harm caused when a patient's intention to control an external device fails as well as privacy and confidentiality of patients' data are some of the challenges faced by BCI in healthcare. Nevertheless, significant attention has not been paid to the challenges that hinder the implementation of BCI in healthcare.

Aims: Consequently, this paper examines the general overview and components of BCI. The applications and challenges of BCI in healthcare are also appraised in this study.

Methodology: Relevant literatures relating to the subject matter were reviewed. The literatures were sought in three scientific electronic databases namely CiteseerX, Science Direct and Google scholar. Furthermore, the Google search engine was used to search for documents and WebPages that contained relevant references for the study. The literatures reviewed were between 1974 and 2018.

Results: The study showed that BCI assists people living with disability to acquire relevant skills and knowledge, diagnose and manage depression, communicate, move and interact socially. The study also revealed that standardization, usability and legal issues are some of the challenges that affect the social acceptability of BCIs in healthcare.

Conclusion: The study suggests that there must be a policy that will protect the privacy and confidentiality of patients' data obtained from BCI. The study also recommends that the comfort and safety of patients must be considered during the operation of a BCI technology. Furthermore, the study suggests that the generation of personal identification number (PIN) can make BCI applications used in healthcare less prone to fraud.

Keywords: Brain; computer; brain computer interface; healthcare; motor disabilities.

1. INTRODUCTION

There are different interfaces that facilitate the interaction of human beings with the computer. Typical examples of these interfaces include keyboard, mouse, pen and touch screen technology. These devices characteristically involve physical interaction with human beings such as touching. However, in recent times, other ways of establishing connection between human beings and the computer without touching have been developed. This mode of interaction is usually referred to as human-computer touchless interface or natural user interface [1]. Human-computer touchless interface provides capabilities for facial recognition, voice recognition and motion capture. Hence, physically disabled or locked in syndrome patients may find it difficult to interact or communicate with the computer either through speech, gesture, or touch [2]. Locked in syndrome otherwise known as pseudocoma is a term that is used to describe a condition in which a patient cannot move or communicate verbally as a result of the complete paralysis of nearly all voluntary muscles except for the movements and blinking of the eyes. It is caused by the infarcts of the anterior part of the pons cerebri [3].

One of the major ways of facilitating communication between locked in syndrome patients and the computer is through brain computer interface (BCI) otherwise known as brain machine interface (BMI). There are diverse definitions for BCI. Generally, a BCI can be defined as a computer based system that acquires and processes brain signals. Traditionally, a BCI is defined as a direct connection between a computer and the brain. Nicolas-Alonso and Gomez-Gil [4] define a BCI as a hardware and software communication system which enables human beings to interact with their surroundings without the involvement of peripheral nerves and muscles, and by using control signals generated from electroencephalographic activity. In Jung's terms, a BCI is a system which takes a bio-signal measured from a person and predicts in real time or on a single-trial basis an abstract aspect of the person's attention or intention as well as neurological and cognitive states [5]. A BCI according to Mak and Wolpaw [6] is a communication or a control system that allows real-time interaction between the human brain and external devices such as wheelchair, robot and artificial limb. These devices transmit and receive signals from the brain which they use to restore damaged sensory organs, control external devices and gather information on user intentions. Mak and Wolpaw [6] emphasized that a BCI allows a person to communicate with or control the external world without using peripheral nerves and muscles. Succinctly, the major function of a BCI system is to measure and analyze brain signals, interpret the measured data and translate the interpreted data into actions that can be used to control the computer and other external devices [7,8]. A BCI can also be used to repair the cognitive and sensory-motor functions of human beings. It provides communication capabilities to its users and also assists users suffering from motor disabilities to control assistive devices such as wheelchairs, artificial limbs or mouse cursor by mere mental thoughts. It is however important to note that a BCI is not a mind reading machine.

The use of BCI is highly significant in healthcare. For instance, it has been applied in the design of a drowsiness detection system [9]. It has also been used to assist partially or fully-disabled people for navigation through robotic arms and legs. It helps paralyzed individuals to use their heads to play games [10]. BCI aids patients to navigate through the web with their brains [11]. BCI technologies have also been used to restore vision to the blind by connecting an external camera to their brain [12,13]. Hence, BCI can be seen as a major technological breakthrough for individuals that are physically challenged. BCI technologies are however bedeviled by several limitations despite their numerous advantages. For instance, ethical issues such as the risk of infection or hemorrhage, psychological harm caused when a patient's intention to control an external device fails, frequent mistakes from a BCI used for typing, unintended movement of a robot arm or a wheel chair as well as privacy and confidentiality of patients' information are some of the major challenges of BCI in healthcare. In addition, the reliability of BCI system is a major limitation confronting the effective use of BCI systems in the healthcare system. This is because the error rate of BCI technology is high. This is usually as a result of low signal strength extracted from the brain [11]. Other challenges confronting BCI technologies range from legal issues, usability problems to low social acceptability in the society. Nevertheless, not much attention been paid to the challenges that limit the implementation of BCI in healthcare. Consequently, this paper examines the general overview and the basic components of a standard BCI. This study also takes a look at the various techniques of extracting signals from the brain. The advantages as well as the limitations of BCI technologies are examined in this study. Ethical issues relating to BCI are viewed in line with the healthcare ethical principles of Tom Beauchamp and James Childress. Furthermore, legal and usability challenges of BCI are major points discussed in this paper.

The remainder of the paper is organized as follows: section 2 presents the research methodology, section 3 deals with the general overview of BCI; section 4 reviews the components of BCI. Section 5 is an overview of signal acquisition methods in BCI. Section 6 discusses the applications of BCI in healthcare, while section 7 examines the challenges of BCI in healthcare. Section 8 provides a list of recommendations that will facilitate the effective use of BCI in healthcare while section 9 concludes the study.

2. METHODOLOGY

Relevant literatures relating to the subject matter were reviewed. The literatures were sought in three scientific electronic databases namely CiteseerX, Science Direct and Google scholar. Furthermore, the Google search engine was used to search for documents and WebPages that contained relevant references for the study. The literatures reviewed were between 1974 and 2018.

3. OVERVIEW OF BCI

The term brain-computer interface (BCI) was first introduced by Vidal Jacques J. in 1973 [14]. However, this technology can be traced to the early electrophysiology laboratory and the first reading of electroencephalography (EEG) by Hans Berger in 1921 [15]. Nonetheless, Dr. Grey Walter was reported to have been the first to use BCI technology to connect electrodes to the brain of a patient undergoing surgery [16]. BCI is multidisciplinary field that draws its research links from neuroscience, applied mathematics, psychology, clinical rehabilitation, engineering, psychology, clinical neurology and computer science [17]. It is a branch of Computer Science that springs up from Artificial Intelligence majorly from Robotics Engineering and Human Computer Interaction. BCI is however the most recent development in the field of Human Computer Interaction [18].

A BCI has been succinctly defined as the direct connection and communication between the brain and the computer as well as other external devices such as intelligent wheelchairs [18,19]. A BCI can also be viewed as a device that translates the signals obtained from the brain into an action that can be performed by the computer. In other words, a BCI is only limited to systems that deploy signals from the brain, hence systems that are nerves, muscles or voice activated are not considered as BCI [20]. The signals obtained from the brain could be electrophysiological, magnetic, or metabolic in nature [18]. In a BCI system, human intentions are usually obtained from these signals [6]. These signals according to Mak and Wolpaw [6] are translated into digital commands that are used to accomplish the intentions of the users such as the control of a computer cursor or a wheelchair. This task is usually achieved with the aim of advanced algorithms [21]. BCI is however not limited to the human brain [22]. In the late 1960's, BCI was used for a study that involved the brain of a monkey. The monkey in this study was used for controlling a meter needle [23]. In addition, the brains of two rats were used to exchange information through an interface in 2012 [24].

Diverse authors have classified BCI into different categories. For instance, Venthur [25] emphasized that BCI can be categorized into two. These include the attention based BCI and the motor imagery BCI. In the attention based BCI, the user employs different stimuli such as visual, tactile or auditory to produce brain patterns which are required to perform specific tasks [8]. However, the visual based attention BCI is the most prevalent [25]. The visual based attention BCI uses two brain patterns to evoke an action. These include event-related potentials (ERP) and steady-state visually evoked potentials (SSVEP). The difference between the ERP and SSVEP is that the stimuli in ERP are usually presented successively while the stimuli in SSVEP are presented continuously [25]. As the name implies, a motor imagery based BCI can be defined as a system that performs an action by the imagination of a motor movement such as the movement of a limb. Jung [5] and Minkyu et al. [26] classified BCI into three. These include active BCI, reactive BCI and passive or affective BCI. In active BCI, a user directly and consciously controls an application through the outputs obtained from the activity of the brain independent of an external event. In a reactive BCI, an application is indirectly controlled by the activity of the user's brain in reaction to an external event while passive or affective BCI obtains the output for controlling an application from the spontaneous activity of the brain without the voluntary control of the user. A BCI according to Nicolas-Alonso and Gomez-Gil [4] can be categorized as synchronous and asynchronous. In synchronous BCI, the system gives a cue to users before a motor imagery is performed, hence it is also known as cue based BCI. In asynchronous BCI, the user is able to perform motor imagery in a self paced manner; this type of BCI is also known as self paced BCI. BCIs can also be classified as independent and dependent [27]. According to Chan et al. [28], an independent BCI does not use the peripheral nerves or muscles to generate brain activity that is necessary to carry out a task while a dependent BCI depends on peripheral nerves or muscles to generate brain activity that is necessary to carry out a task. Another typical category of BCI is endogenous and exogenous BCI [4]. In endogenous BCI, the users are extensively trained on how to produce specific brain patterns required for performing a task while exogenous BCI do not require extensive training on the production of specific brain patterns. Typical examples of exogenous brain signals include SSVEPs and P300. Table 1 summarizes the classification of BCI.

For a system to be considered a BCI, it must possess the following characteristics:

i. It must obtain its signals solely from brain activities.
ii. A BCI system must provide relevant feedback to its users so that the users will know if their intentions have been successfully carried out or not.
iii. A BCI system must possess a high response time, that is, there must be no delay between the time the user presents his intention and the time the system performs the action. In other words, the interaction between a BCI system, the outside world and its users must be in a real time manner [29,30].

3.1 Techniques of BCI

There are different types of paradigms in BCI. These paradigms include event related potentials (ERP), slow cortical potentials (SCP), sensorimotor rhythms, motor imagery, oscillatory EEG activity and Visual Evoked Potential (VEP).

3.1.1 Event related potentials (ERP)

Hoffman et al. [31] described an ERP as stereotyped, spatio-temporal patterns of brain activity that occurs in a time-locked event usually after the presentation of a stimulus, before the execution of a movement, or after the detection of a novel stimulus. An ERP can simply be defined as an electrophysiological response to an internal or external stimulus [32]. A typical

Table 1. Classification of BCI

Types of BCI	Description
Attention based BCI	Produces brain patterns through visual, tactile or the auditory system
Motor imagery	Works by the imagination of a motor movement
Active BCI	User directly and consciously controls an application through the outputs obtained from the activity of the brain
Reactive BCI	An application is indirectly controlled by the activity of the user's brain
Passive BCI	Obtains the output for controlling an application from the spontaneous activity of the brain without the voluntary control of the user
Synchronous or cue based	Users are given cue to before a motor imagery is performed
Asynchronous or self paced based	Users perform motor imagery in a self paced manner
Independent dependent	Does not depend on peripheral nerves or muscles to generate brain activity depends on peripheral nerves or muscles
Endogenous	The users are extensively trained on how to produce specific brain patterns
Exogenous	Do not require extensive training on the production of specific brain patterns

example of an ERP is the P300 speller. The P300 is a communication device that allows users to spell characters. The P300 speller was first introduced by Farwell et al. [33] in 1988. The classical P300-Speller layout is presented to the user on a 6 × 6 matrix of symbols comprising of 26 letters of the alphabet and 10 digits (0-9) on a computer screen as depicted in Fig. 1.

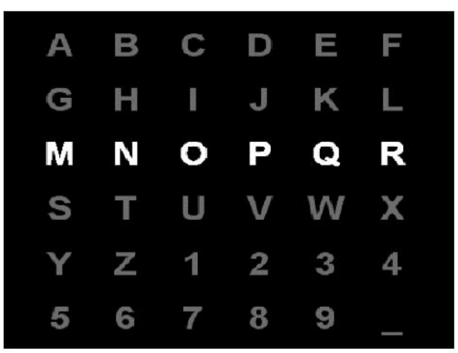

Fig. 1. A classical P300 speller [34]

Fazel-Rezai [32] emphasized that the P300 speller is involved with the process of memory modification or learning; it is relatively fast, effective for most users, straightforward and does not require intensive training. However, Cecotti [34] pointed out that most P300 spellers are not robust and they do not meet user's requirements due to un-adapted end user interface.

3.1.2 Slow cortical potentials

Slow cortical potentials (SCP) are slow voltage shifts in electroencephalography (EEG) that are below 1 Hz [35]. SCPs are usually associated with changes in the level of cortical activity of the brain [4]. For instance, when the value of the SCP is positive, it implies that there is a reduction in the activity in the individual cell while a negative SCP indicates an increased neuronal activity [36]. One basic advantage of the SCP is that it can be used by both healthy and paralyzed users to control external devices. SCP however requires extensive training procedures.

3.1.3 Visual evoked potentials (VEP)

Visual Evoked Potential (VEP) usually occurs in the visual cortex of the brain after receiving a visual stimulus. Hence, classical VEPs are not suitable for paralyzed individuals with oculomotor impairments. A typical example of VEP is the Steady State Visual Evoked Potential (SSVEP). SSVEP are usually acquired from visual stimulus that is obtained from light-emitting diodes (LEDs), cathode-ray tube (CRT) monitors or liquid crystal display (LCD) [4]. However, LEDs perform better than LCD or CRT because they produce a large number of visual stimuli [4]. The visual stimulus represents an action such as prosthesis movement, icons and/or alphabet letters selection. SSVEP allows users to select their targets by eye gaze while the brain pattern corresponding to the frequency of the visual stimuli is generated in the user's brain and is translated and executed as the user's desired command [8]. Hence, SSVEP is inappropriate for patients with advanced stages of Amyotrophic Lateral Sclerosis (ALS) or with uncontrollable eye or neck movements [4]. However, SSVEP is only suitable for users with healthy vision and eye movements [37]. The advantages of SSVEP include high signal-to-noise ratio, minimum training prerequisites and reliable communication paradigm for non-invasive BCI [37]. There are also spellers based on SSVEP. SSVEP spellers are based on oscillating visual stimulus [38]. SSVEP spellers perform better and are more reliable than the P300 speller. A typical example of a SSVEP speller is the Bremen-BCI speller. The Bremen-BCI speller has a graphical user interface (GUI) that is composed of a virtual keyboard with 32 characters located in the middle of the screen [34]. The GUI is composed of five white boxes at the outer edges and upper left corner of the screen. These boxes represents "left", "right", "up", "down", and "select" [34]. Fig. 2 depicts the Bremen-BCI speller.

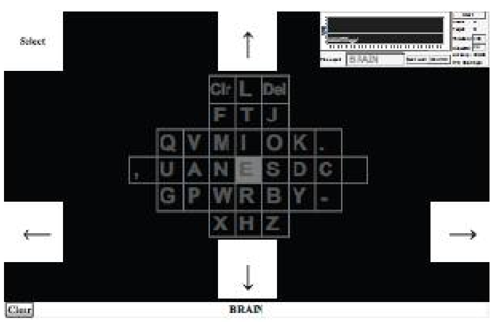

Fig. 2. The GUI of Bremen-BCI speller [34]

3.1.4 Sensorimotor rhythms

Sensorimotor rhythms, is also referred to as mu and beta rhythms because it consists of mu and beta rhythms, which are oscillations in the brain activity localized in the mu or Rolandic band (7–13 Hz) and the beta band (13–30 Hz) [4]. According to Nicolas-Alonso and Gomez-Gil [12], sensorimotor rhythms are related to motor imagery without any actual movement [4].

3.1.5 Motor imagery

Motor imagery is usually based on the imagination of the right or left hand or foot movement which results in the production of event related synchronization or de-synchronization over the sensorimotor cortex [39]. Motor imagery BCIs are more accurate than ERP but they require more training. It is important to note that there are motor imagery based spellers. A typical example of a motor imagery based speller was proposed at the Artificial Intelligence and Robotics Laboratory (AIRLab), Department of Electronics and Information, Politecnico di Milano, the Technical University of Milan, Italy [34]. The AIRLab speller has 27 characters; it also contains features that support word suggestions and disabled improbable symbols [34]. Fig. 3 shows the GUI of the AIRLab speller. Cecotti [34] emphazed that the speller has two mental states which include imagined right hand movement and imagined right foot movement. The speller has a circle which contains an arrow used for selecting characters. The arrow turns clockwise when a right hand movement is imagined while the rotation of the arrow stops and moves to the desired field when a foot movement is imagined [34].

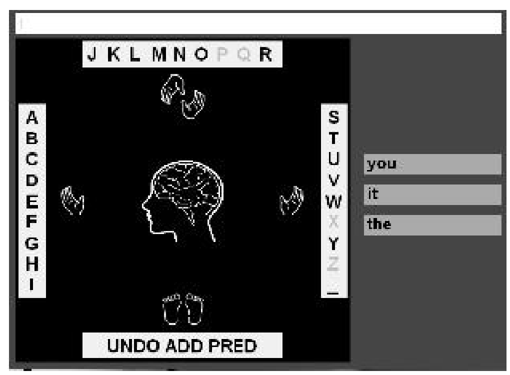

Fig. 3. The GUI of the AIRLab speller [34]

3.1.6 Oscillatory EEG activity

Oscillatory EEG activity results from a network of neurons which causes feedback loops. Examples of oscillatory EEG activity include the Rolandic mu-rhythm, in the range 10–12 Hz, and the central beta rhythm, in the range of 14–18 Hz [18].

4. COMPONENTS OF BCI

A typical BCI is usually composed of four essential elements namely signal acquisition, signal processing, data manipulation and feedback. The elements of a typical BCI system are briefly discussed below:

4.1 Signal Acquisition

Signal acquisition according to Mak and Wolpaw [6] can be defined as the measurement of the neurophysiological state of the brain. It is also the process of obtaining electrical signals from the brain. Electrical signals can be obtained either from the scalp, the surface of the brain, or from neural activity via electrodes [18]. The signals obtained are usually amplified because the signal strength received from the brain is usually low.

4.2 Signal Processing

This involves the analysis of the acquired signals in order to get control signals. Signal processing can be done in three basic ways which include pre-processing, feature extraction and signal classification or signal translation.

4.2.1 Signal pre-processing

Signal pre-processing involves the enhancement of the signals obtained from the brain.

4.2.2 Feature extraction

Feature extraction is basically the process of extracting specific features from brain signals. Feature extraction is usually done to remove electrical noise and undesirable signals from the acquired signals. There are diverse methods of extracting features in BCI. Typical examples of these techniques include parametric and non-parametric techniques [4]. Examples of parametric approaches include the Autoregressive (AR) and the Adaptive Autoregressive (AAR) methods. The AR model according to Jeyabalan et al. [35] is more attractive than the AAR methods because it has the capability to summarize information concisely and translates them into feature vectors [35]. However, AR is unsuitable for non-stationary signals while the AAR techniques are suitable for revealing non-stationary time variations of brain signals [4]. Another method of extracting signals in BCI is Principal Component Analysis (PCA). PCA can be described as statistical method that relies on orthogonal transformation to convert a set of correlated observations into a set of uncorrelated variables called principal components [4]. PCA computes the covariance matrix, C, of a training data p= [p_1………..p^n] as shown in Equation (1):

$$C = \sum_{l=1}^{n}(p_i - m)(p_i - m) \quad (1)$$

Where C is the covariance matrix, p_i is the training sample, n is the number of samples and m is the mean vector which is computed as:

$$m = \frac{1}{n}\sum_{i=1}^{n} p_i \quad (2)$$

PCA then computes the eigen values of the eigen vectors of the covariance matrix. It is important to note that the eigenvectors with the highest eigenvalue represents the principal components of the training dataset p [4]. The number of principal components is however usually less than or equal to the number of original dataset. Consequently, PCA is used for reducing the dimension of features.

4.2.3 Signal classification

Signal classification involves the translation of the filtered signals into device commands which are responsible for carrying out the users' intentions [18]. Examples of signal classification methods include Linear Discriminant Analysis (LDA). LDA is a simple classifier that is used to classify patterns into two or more classes. For a two class pattern classification, LDA defines a linear discrimination function which represents a hyperplane in the feature space while in feature classification that involves more than two classes; several hyperplanes are used [4]. This can be mathematically expressed as shown in Equation 3.

$$g(w) = w^t x + w_0 \quad (3)$$

Where w is the weight vector, $\boldsymbol{x}$ is the input feature vector and w_0 is a threshold. LDA has a high rate of accuracy without high computation requirements [4].

4.3 Data Manipulation

Data manipulation involves the management of the device commands in a way that will suit the output devices.

4.4 Feedback

The function of the feedback is to inform the users if their intentions have been carried out. There are two types of feedback in BCI [29]. These include direct feedback and indirect feedback. The direct feedback provides information about the level of the brain activity while the indirect feedback provides information about the result of a self initiated BCI action such as the movement of a robotic arm [29].

The components of a BCI are illustrated in Fig. 4.

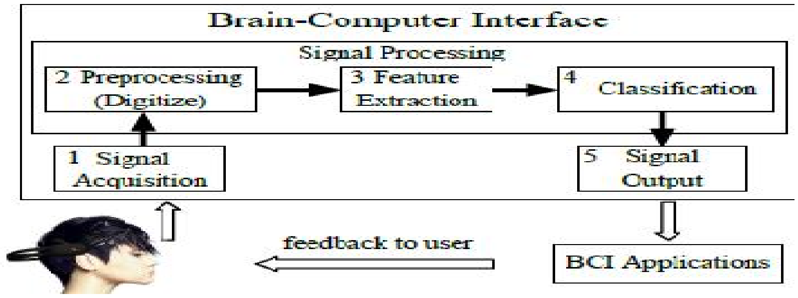

Fig. 4. Components of BCI [40]

5. SIGNAL ACQUISITION METHODS IN BCI

There are three methods of acquiring signals from the brain. These include the invasive BCI, partially invasive BCI and non-invasive BCI. This is as depicted in Fig. 5.

5.1 Invasive BCI

These are devices that use sensors, electrodes or chemical molecules implanted directly into the grey matter of the brain during neurosurgery to capture brain signals. The signals obtained from the electrodes in invasive BCI are called the electrocorticogram (ECoG) [41]. There are two types of ECoG. These include epidural electrocorticogram and subdural electrocorticogram. The epidural electrocorticogram are those signals that are obtained from electrodes placed on the surface of the cortex outside the dura mater of the brain while subdural electrocorticogram are signals obtained under the dura mater of the brain [4]. Invasive BCI has the most quality signal strength; they are more accurate and less noisy [42]. Invasive BCI are however very risky because they are prone to scar tissue build up. Hence, BCI researches have only been implemented in animal models [43]. There are however two types of invasive BCI. These include the single unit and the multi-unit BCI [27]. Single unit invasive technique captures signal from a single area of brain cells while multi-unit invasive technique captures signal from multiple areas of the brain. Fig. 6 is an illustration of an invasive BCI electrode.

5.2 Partially Invasive BCI

Partially invasive BCI uses electrodes that are usually embedded in a thin plastic pad placed above the cortex as shown in Fig. 7. Hence, it can be said that in partially invasive BCI, the electrodes are implanted inside the skull but outside the brain. However, the signal strength in partially invasive BCI is lower than that of invasive BCI and the risk of forming scar tissue is lower than the invasive BCI [44].

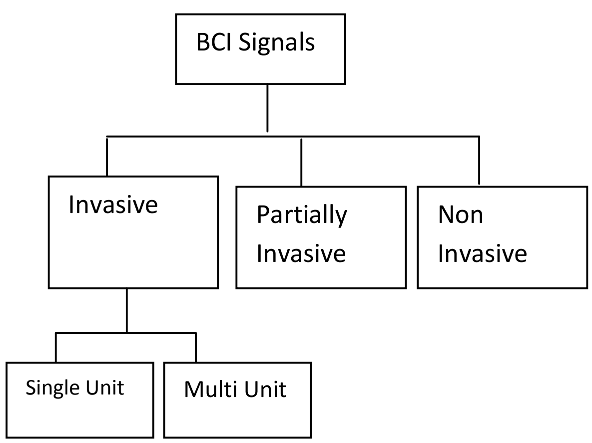

Fig. 5. Methods of acquiring signals in BCI [30]

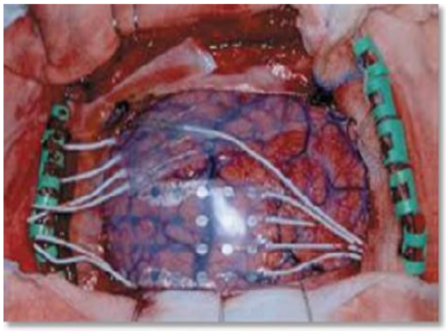

Fig. 6. Invasive BCI electrodes [31]

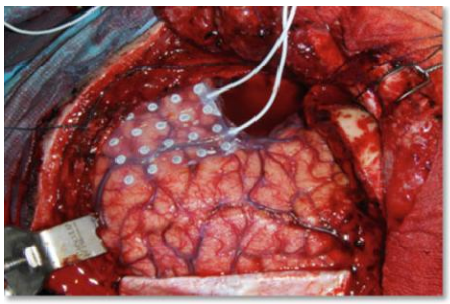

Fig. 7. Partially invasive BCI electrodes [31]

5.3 Non Invasive BCI

In non-invasive BCI, medical scanning devices or sensors are usually mounted on a cap or a headband to read brain signals as illustrated in Fig. 8. Thus, non-invasive BCI do not require intracranial surgery and implantation of a device in the brain. This type of BCI is usually considered the safest form of BCI because they do not involve a risk of infection or hemorrhage [45]. They are also less expensive than the invasive and partially invasive BCI. The strength of the signal generated in non-invasive is lower than the invasive and partially invasive BCI. The major disadvantage of non-invasive BCI is that the signals are attenuated in the process of passing through the skull, dura and scalp. This leads to loss of information [20]. Non-invasive BCI uses functional Magneto-Resonance Imaging (fMRI), Positron Electron Tomography (PET), functional near infra-red spectroscopy (fNIRS) MagnetoEncephaloGraphy (MEG), electroencephalography (EEG) and Single Photon Emission Computed Tomography (SPECT) to capture brain signals [46]. EEG has however been regarded as one of the most promising signals because they are easy to capture and analyze [47].

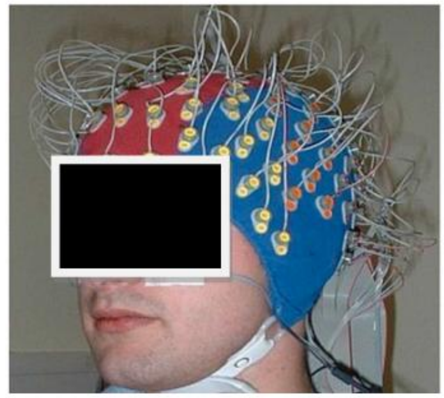

Fig. 8. Non invasive BCI electrodes [5]

6. APPLICATIONS OF BCI

BCI has been used applied in several ways to assist people living with depression, disability, disorders of consciousness (DOC) and communication problems. Typical examples of people who fall into this category include people who suffer from cerebral palsy, brainstem stroke, spinal cord injuries, muscular dystrophies, or chronic peripheral neuropathies and Amyotrophic Lateral sclerosis (ALS). These diseases usually result in the loss of muscle functions which results in a situation where the patients' cognitive functions are preserved but totally locked in to their bodies [48]. However, BCI systems provide locked in syndrome patients with the ability to communicate words, letters and commands to a computer interface which translates them into a computing output that the user has the ability to control. Hence, BCI systems are used to reduce the cost of healthcare and to improve the health status of people with severe motor disabilities. This section critically examines the benefits of BCI in healthcare.

6.1 Locomotion

Locomotion refers to the ability to move from one place to another. However, people with severe motor disabilities such as ALS, polyneuropathy, amputees and paraplegia paralyzed patients find it difficult to move. Hence, BCI technologies like voice controlled wheelchair, remote and joystick controlled wheelchair, BCI-driven wheelchairs, robotic arms and legs as well as prosthetic devices such as prosthetic knee and hands have been developed to assist patients' suffering from mobility challenges [30,49,50]. This increases their level of independence.

6.2 Entertainment

BCI provides an opportunity for people with severe motor deficiency to play games in order to fulfill their psychological needs. BCI also provides opportunities for disabled patients to relax [51]. For example, a virtual reality game, MindBalance was developed at the University College, Dublin and Media Laboratory Europe for people with limited body movement. Mind balance uses EEG, cerebral data nodes and Bluetooth. In addition Tan and Nijholt developed the brain ball game that is used to reduce the stress level of patients [52].

6.3 Restoration

BCI technologies are also used to restore sensory and motor functions of individuals with neurological diseases in order to ease their psychological and social suffering. For instance, Krishnaveni et al. [13] reported that bionic eyes can restore the sight of people with loss of vision. Movement restoration can also be achieved through the use of prostheses [53]. In line with this, Muller et al. [54] developed a neuroprosthetic device for restoring the grasp function of people with spinal cord injuries. Furthermore, Hochberg et al. [29] emphasized that bidirectional feedback between a user and a BCI results in physical changes that restore motor functions and communication control to individuals who are neurologically compromised.

6.4 Communication

BCI systems are used for assisting locked in patients to communicate. BCI applications for communication include spelling devices (such as P300 speller), environmental control and Functional Electric Stimulation (FES) or prosthetic devices [55,56]. BCI devices also provide its users with the ability to select icons on a computer screen as well as perform basic word processing [57]. Furthermore, BCI applications allow individuals suffering from neurological disorders to use the World Wide Web through their brains [11].

6.5 Environmental Control

BCI systems have been used to improve the quality of life of locked-in syndrome patients [58]. For instance, with BCI, patients can control domestic environmental devices such as thermostat, lights and television thereby increasing their level of independence [4].

6.6 Movement Control

BCI systems have been used by patients with motor disabilities to control their movement. For instance, the movement of a cursor by a patient with his brain will enable him control his environment [59,60]. Furthermore, BCI technologies can be used to control the movement of a robot. For instance, Carmena et al. [61] used a primate to control the movement of a robot's arm through BCI.

6.7 Rehabilitation

Regaining functional independence is very important for patients with neurological disorders and mobility issues such as stroke. Stroke is one of the major health issues affecting people globally. It is the leading cause of disability among adults and it usually results in a high level of dependence among the elderly [62]. However, one of the major methods of managing stroke patients is neurorehabilitation [63]. BCI is used for neurorehabilitation to assist stroke patients achieve optimal level of motor function and independence. However, the use of BCIs in neurorehabilitation is still in its early stage [30].

6.8 Education

Education is the acquisition of knowledge, skills and values that makes an individual an independent and useful entity in the society. BCI is used to teach disabled individuals how to learn spelling, play games and use diverse applications such as word processors. In addition, BCI can be used to monitor the attention and concentration of individuals during learning processes [30].

6.9 Social Interaction

In recent times, BCI technologies are becoming portable and less complex; consequently they are now used in mobile applications to obtain emotional data from users which can be added to social media posts [32]. Hence, this creates an awareness of the emotional state of the patient.

6.10 Pain Management

BCI technologies can serve as a useful tool for managing chronic pain. For instance, a study conducted by Yoshida et al. [64] showed that BCI applications have the ability to provide relief for patients with persistent neuropatic pain, thereby increasing their quality of life.

6.11 Depression Diagnosis and Management

The assessment of depression is usually based on clinical observations and patients' self-reports. However, BCI technologies are used to obtain emotional data from users. Hence, BCI can be easily used to diagnose depression in patients through the emotional data obtained from the patients. Hence, adequate treatment can be given to such patients in a timely manner.

6.12 Schizophrenia Management

Schizophrenia is a severe mental disorder that affects the ability of a person to think, feel and behave well. Studies have shown that EEG neurofeedback can be used to treat schizophrenia [65]. There is however limited research on the use of BCI systems to treat schizophrenia [5].

6.13 Monitoring of Sleep and Emotions

BCI is used to monitor the sleep patterns as well as the emotions of patients.

6.14 Reduces the Cost of Healthcare

BCIs reduce the cost of healthcare by reducing the need for constant supervision by rehabilitation therapists [19].

7. CHALLENGES OF BCI IN HEALTHCARE

The applications of BCI in healthcare range from pain management, social interaction, to rehabilitation, movement control and the provision of communication aids. BCI is however not a widely deployed technology in healthcare because there are numerous challenges that are associated with it. These challenges include ethical challenges, legal issues, design issues, safety usability issues, acceptability and appropriateness. Hence, this section critically examines the factors that hinder the effective use of BCI in healthcare.

7.1 Ethical Challenges

The term ethics is derived from the Greek word 'ethos' which denotes customs, habits and morals of a people [66]. Ethics is a branch of philosophy that deals with the investigation of the values and virtues that are paramount to a society [67]. On the other hand, medical ethics is based on a series of ethical principles that are particularly relevant to medical practice and patient care [68]. Medical ethics are basically used to guide healthcare decisions, and the way healthcare providers interact with patients and their families. Beauchamp and Childress [69] introduced four basic principles of medical ethics which include respect for autonomy, non-maleficence, beneficence and justice. This section discusses the ethical challenges confronting the efficient use of BCI in healthcare in line with Beauchamp and Childress [59] basic principles of medical ethics. This is because significant attention has not been paid to ethical issues that concern the implementation of BCI in healthcare [70].

7.1.1 Respect for autonomy

The term autonomy is derived from the Greek word "autonomonos". "Auto" means self while "nomonos" means rule. Hence, the term autonomy means self-rule [71]. In healthcare parlance, autonomy refers to the ability of healthcare providers to involve the patients in the decisions that concern their care. Hence, Snyder and Gauthier [58] define autonomy in the context of healthcare as the capacity to make and communicate one's decisions. Hence, it is important to involve patients by informing and educating them on all measures of their care. Hence, Erbguth [72] emphasized that not informing concerned patients on the expected benefits and potential risks of BCI is a lack of respect to autonomy. It is however difficult to get informed consent from individuals who have difficulty in communicating.

7.1.2 Non-maleficience

The principle of non-maleficence is derived from the ancient maxim primum non nocere which means "First, do no harm, benefit only" [71]. Hence, this principle is of the view that healthcare providers must not harm their patients. Harm in this respect refers to anything that worsens the condition of the patient such as the presence of pain, inadequate medical facilities and staff, inconvenience, expense, suffering, disease, disability, and death [71]. In addition, the best interest of the patient also includes the ability of healthcare providers to promote the well-being of the patient [68]. In general, BCI technologies are used to promote the well being of patients; however, the misuse associated with this technology remains largely unexplored [73]. For instance, Ienca and Haselager [73] reported that BCI technologies are vulnerable to a cybercrime known as neurocrime. Neurocrime according to Ienca and Haselager [73] refers to cybercriminal activities enabled by the misuse of neural devices. Neurocriminal activities in BCI typically involve the modification or disruption of the functions in the devices that interface brain computation without the patients' consent. Resultant harm caused by neurocrime include the deprivation of the patients to use their motor abilities, emotional instability such as fear and psychological distress, mental harm as well as threat to the patients lives. Furthermore, invasive BCI technologies such as electrocorticography (ECoG), electrodes are implanted epidurally or subdurally in the human brain. Nonetheless, ECoG are prone to cranial smearing, infection and hemorrhage [35]. In addition, the use of BCI can result in psychological harm when a patient fails to accomplish an intended task. Consequently, the use of BCI in healthcare is a challenge.

7.1.3 Beneficence

Beneficence according to Snyder and Gauthier [68] refers to the ability of healthcare providers to act in the best interests of the patient. Synder and Gauthier [68] in this regard, refer to best interest as the ability of healthcare providers to prevent and remove harm from the patient. Conversely, Summers [71] emphasized that beneficence implies more than just avoiding doing harm. Summers [71] therefore viewed beneficence as a principle that involves taking positive and direct steps to helping others. Hence, to ensure beneficence in healthcare, healthcare professionals must sustain a high level of skills and knowledge in the use of current and best medical practices. However, one of the major challenges facing the use of BCI in healthcare is the high cost involved in training healthcare professionals. Hence, BCI technologies are not widely deployed in healthcare despite their significant impacts on healthcare delivery.

7.1.4 Justice

The principle of justice refers to the ability of healthcare resources to be distributed in a fair way among the members of society. However, BCI technologies are not readily available to those that need them. This is because of the individualized nature of the technology. For instance, Erbguth [62] reported that only one-third of neurological centers in Germany offer invasive ventilation for patients with motoneuron disease.

7.2 Legal Challenges

Law in respect to technology can be defined as a method of managing technological risks [74]. Some of the legal challenges confronting the effective use of BCI include freedom of privacy, freedom of thought and liability issues [16].

7.2.1 Freedom of privacy

Privacy refers to the right of individuals to prevent their information from being revealed to others; the claim of individuals to avoid surveillance or interference from other individuals, organizations or the government [75]. However, BCI technologies require the collection and processing of sensitive information from patients while monitoring neural activities in the brain. Hence, BCI systems are prone to attacks such as passive eavesdropping, active interception, denial of service, data modification [66].

7.2.2 Freedom of thought

Thought can be viewed as an idea or opinion that is produced by reasoning. Freedom of thought on the other hand is referred to as the ability of an individual to think freely, change his religion and have a free conscience. It is however important to recall that BCI systems enable patients with motor disability to control assistive devices such as wheelchairs, artificial limb or mouse cursor by mere mental thoughts. Hence, Krausová [16] viewed BCI technologies as a threat to the freedom of human thought and a violation of human right. This is because the thought of the individual is limited to control a particular device at an instance.

7.2.3 Liability issues

This principle clarifies the individual that will bear the responsibility for a BCI failure in the case of software errors, mechanical failures such as accident, and unexpected harmful side-effects.

7.3 Standardization Issues

Standards are agreed-upon specifications that allow independently manufactured products, whether physical or digital to work together [76].

However, there is no common file format for exchanging data obtained via BCI amongst healthcare providers and patients [18]. Hence, BCI applications are not interoperable.

7.4 Reliability Issues

According to Pattnaik and Jay Sarraf [46], the reliability of most BCI systems is poor. One of the factors that contribute to the poor reliability of BCI systems is the low strength of signal usually extracted from the brain. Hence, signal amplification is usually required in BCI applications. However, many of the amplifiers used in most BCI systems are not good [18].

7.5 Accuracy

The percentage error rate is usually high in most BCI systems because of the low signal strength obtained from the brain.

7.6 Time Consuming Training Process

The successful use of BCI applications requires the acquisition of skills that must be effectively maintained [38]. Hence, patients with severe paralysis are required to be effectively trained on the use of BCI to operate a motor task. However, the training process is usually time consuming [77].

7.7 Usability Issues

In general, usability refers to how easy it is for users to accurately and efficiently accomplish a task while using a system. Hence, usability expresses how well the user's goal can be achieved with a system in a specific context. Mayhew [78] also defines usability as how well a system supports the user's real life tasks, how easy it is for diverse user groups to learn the use of a system, how efficient the system is for frequent users, how easy it is for occasional users to remember the functionalities of the system, how satisfied the users are with the system and how easy it is for the system users to understand what the system does. Most BCI systems however encounter low usability [32]. Some of the factors contributing to the low usability of BCI systems include aesthetics, battery life, device weight and rapid fatigue of users during the deployment of BCI which is usually caused by a high concentration on a mental task or prescribed stimuli [42] Hence, the social acceptability of BCIs is generally low.

7.8 High Cost of Procurement and Maintenance

The cost of procuring many BCI systems is high [61]. In addition, the cost of maintaining BCI applications is very high [20]. Hence, BCI applications are not generally affordable to individuals with motor deficiencies.

8. RECOMMENDATIONS FOR THE EFFECTIVE USE OF BCI IN HEALTHCARE

BCIs are generally used to promote the quality of life of severely paralyzed patients by enhancing their communication and locomotion capabilities. BCI technologies also restore motor functions in severe paralyzed patients. It facilitates social interaction amongst disabled individuals and their families. It can also be used in the management of pain. However, several challenges hinder the effective use of BCI technologies in healthcare. These challenges range from ethical issues, legal issues, accuracy to usability challenges and standardization issues. Hence, the social acceptability of BCI technologies is generally low. Consequently, this paper recommends the following for BCI stakeholders such as patients, healthcare providers, government, policymakers, and device manufacturers.

i. Healthcare providers must give detailed, relevant and truthful information about BCI to patients, and patients should be made to make a voluntary decision on the use of BCI for their care without coercion or undue influence. Hence, the use of informed consent is very vital for the deployment of BCI systems on locked-in syndrome patients.
ii. Patients must be educated on the applications and limitations of BCI. This is to avoid disappointments from the patients when a BCI system does not perform its task.
iii. For non-invasive BCI, the electrode interface/ cap must be comfortable.
iv. Healthcare providers and patients should be effectively trained on the use of BCI applications such as the spellers.
v. Government and policy makers should make adequate laws to protect patients' information obtained through BCI technologies from malicious individuals. In addition, a legal framework and effective policies that will protect the confidentiality

and privacy of patients' data must be developed. This should be done to eliminate the fears of being exposed since patients that deploy BCI are usually vulnerable.

vi. Patients using BCI should be evaluated on a regular basis to estimate how well their abilities match with the technology. The branch of computing that deals with the evaluation of how a human ability matches with a technology is referred to as neuroergonomics.

vii. This study also recommends the work of Palaniappan and Revett [79] and Palaniappan et al. [80] which emphasized that the generation of personal identification number (PIN) can make BCI applications used in healthcare less prone to fraud. This authentication measure confirms the users' identity.

9. CONCLUSION

A BCI can simply be defined as the direct connection and communication between the brain and the computer as well as other external devices such as intelligent wheelchairs. BCI is applied in several fields such as Education, Entertainment and Healthcare. However, the use of BCI is highly significant in healthcare. This is because BCI systems reduce the cost of healthcare and improve the health status of people with severe motor disabilities. In line with this, this study focuses on the general concept of BCI, the techniques of BCI, signal acquisition methods in BCI and the benefits and problems of BCI in healthcare. The study was based on an extensive review of literature. The result of the review showed that BCI can be used to assist locked in patients to communicate, restore the sensory and motor functions of individuals with neurological diseases, and it can also be used for neurorehabilitation to assist stroke patients achieve optimal level of motor function and independence. The study also revealed that BCI can be used to reduce pain, monitor the sleep patterns and emotions of patients and also assists patients to control domestic environmental devices such as thermostat, lights and television. The study however revealed that accuracy, reliability, standardization issues, privacy and neurocrime are some of the limitations of BCI in healthcare. The study however suggests that healthcare providers and patients should be effectively trained on the use of BCI applications, adequate laws should be enacted to protect patients' information obtained through BCI technologies from malicious individuals and the generation of personal identification number (PIN) to reduce the perpetration of fraud in BCI health care applications are some of the ways of encouraging the use of BCI in healthcare.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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