STM JOURNALS

International Journal of
Brain Sciences

ISSN: 3048-7935
Volume 2, Issue 2, 2025
July–December
DOI (Journal): 10.37591/IJBS

https://journals.stmjournals.com/ijbs

Review IJBS

Mind-Machine Synergy: The Evolution and Future of Brain-Computer Interfaces

V. Basil Hans*

Abstract

Brain-Computer Interfaces (BCIs) represent a transformative technology that enables the direct communication between the human brain and external devices, bypassing the traditional output mechanisms, such as speech or physical movement. BCIs hold the potential to revolutionize fields, such as healthcare, neuroscience, and human-computer interaction by providing new ways to restore lost functions, enhance cognitive abilities, enable seamless communication, and create novel user experiences across various platforms and environments. This article explores the underlying principles of BCIs, including the acquisition of neural signals, advanced signal processing techniques, and the development of various innovative BCI models. We examine the current applications, such as aiding individuals with disabilities, and investigate challenges related to signal accuracy, user training, and ethical considerations. Additionally, we highlight the importance of interdisciplinary collaboration in advancing BCI technologies, from neuroscience to engineering and computer science. Moreover, we discuss the future direction of BCI research, including the advancements in non-invasive technologies, integration with artificial intelligence, and their potential to shape the future of human augmentation and brain-based communication. Through this exploration, we aim to provide a comprehensive overview of the current landscape of BCIs, offering the insights into both their promise and the obstacles that must be overcome for their widespread adoption.

Keywords: Research, human augmentation, functionality, usability, and ethical deployment

INTRODUCTION TO BRAIN-COMPUTER INTERFACES

Brain-Computer Interface, or BCI, is a direct communication pathway established between the brain and an external system without using normal action of output signals. This is a developing scientific area including various scientific disciplines, such as neuroscience, computer technology, artificial intelligence (AI), and robotics. The fundamental purpose of the BCIs is to establish a communication method and a control mechanism in brain dysfunctions seen in patients with an advanced nervous system. There are many applications implemented for BCIs, such as movement control of computer mouse cursors and wheelchairs, writing in virtual keyboards, video game management, robot arm control, relax and entertainment states, web browser commands scrolling up and down, and sending social media status commands, etc. because of the increasing widespread usage of multitasking and information technologies in modern technology, ergonomic and fast communications methods are important in the transfer and sharing process the big size of data . Brain wave changes can be monitored and detected using various equipment and software, and they can control the actions of many objects or systems in human life (changing the way of life in an industrial revolution; huge leaps in electronics). BCIs work to meet speed/robustness/security needs according to real-time push/pull communication application requirements in quantum ad hoc or edge networks, whether for a specialized global or

*Author for Correspondence
V. Basil Hans
E-mail: vhans2011@gmail.com

Research Professor, Department of Management and Commerce, Srinivas University in Mangalore, Karnataka, India

Received Date: March 19, 2025
Accepted Date: May 20, 2025
Published Date: May 26, 2025

Citation: V. Basil Hans. Mind-Machine Synergy: The Evolution and Future of Brain-Computer Interfaces. International Journal of Brain Sciences. 2025; 2(2): 19–31p.

general user population. The study of BCIs is gaining importance while increasing the number of people who need to use the computer or electronic devices without physical contact. These platforms are the control opportunities of devices with thought waves, which are processed in real-time by computer-supported algorithmic methods. Brain Capacitance Swelling/Collapse from Neuronal Firing (BC-SAC) is an unquestionable way to obtain very precise local current information from brain activity, because the number of incident digital signals from the IC pins is always correlated with the characteristics of the invested brain tissues. Researchers have started many projects that touch the brain and scalp electrodes with computers or many artificial objects, which have large and complex electronic circuits containing sensitive chips and sensors after discovering the electric events by brain volume that are well suited for N2D. AI training and algorithm studies accelerated with technological developments can analyze very difficult and complex signals from the brain volume and any real object environment and use these information as a N2C potential in the application requirements in real-time from human or animal brain. There will be ups and downs with decreasing the number of strokes and being out of direct contact with gold-tipped surface electrodes and hybrid applications as a combination of the BCI modeling of the brain's brown volume, communications systems, and VLSI. Modern and smart applications in the sense of brain-managed environments surpass current capabilities and make life easier. For this reason, the software of BCIs is more multifunctional and owner friendly will be needed [1].

HISTORICAL DEVELOPMENT OF BRAIN-COMPUTER INTERFACES

At the beginning of the 20th century, a wide range of devices and experimental methodologies were available to investigate brain activity. The raw and highly unstable brain signals could generate early EEG recordings. Following years of research into the electrical phenomena of the brain, the EEG was finally recorded by Hans Berger in the 1920s. Despite the skepticism and rejection by the scientific community, Berger had successfully demonstrated the existence of the EEG.

In the age of the flower children, of psychedelics and Timothy Leary, of the new beginning of space research and guerilla warfare, humans made their first steps beyond the confinement of our planet. In the turmoil of such beneficial madness, while mankind was apparently proving itself to be capable of miraculous deeds, it also took its first cloaked steps toward a deep understanding of the mechanisms of the brain. As the wheel of history had to turn, around this time instruments evolved that made it possible to further research the endeavors of old and ongoing recondite experiments. As technology progressed, so did neurophysiology; not only could signals be measured with greater spectral resolution and precision, but it was also possible to access an ever completer and more detailed image of the inner and outer mechanics of the brain, both "in vivo" and "in vitro". This, in turn, led to an unprecedented harvest of truths about the nervous system. It was also then when mythological research – looking for the primary nature of things – and technology met, nurturing a child, the first technological artifacts that could be interfaced with brain activity – the brain computer interface [2].

NEUROSCIENCE FUNDAMENTALS FOR BRAIN-COMPUTER INTERFACES

In the bustling environment of a city or at a large family gathering, be it a wedding, birthday or other event, we are often subjected to elevated sound levels. Whether it be the calming sound of specially composed music in a yoga studio or the disruptive traffic noise when stuck on a busy highway, all of these and many other sound experiences have a big influence on our lives. Consequently, problems related to these environmental sounds are of great interest and importance to the research community. The brains of healthy listeners have an extraordinary ability to group, organize and understand complex acoustical scenes by relying on very subtle cues, such as slight intensity differences or temporal changes in sound. Conversely, acoustical problems might be the source of serious limitations and disadvantages in daily life for those suffering severe loss of hearing. One of the pivotal challenging issues in auditory research is trying to make out how the perception of a complex auditory scene is represented in the brain. Over the past two decades, combined with the development of non-invasive neuroimaging and attempts to decode the pattern encoded in human brain activities have yielded fascinating and exciting developments in neurophysiological studies. Hence, in this article, neuroimaging studies that are closely related to the decoding of more natural and complex auditory scenes are reviewed.

As the most complex system in the body by far, the brain is a fitting consortium of billions of neurons entwined in an intricate web of trillions of synapses, all forming highly regulated networks specialized for a myriad of functions. Communication between these networks is thought to be accomplished by the modulation of the timing and frequency of spiking activity in particular cell populations. This communication gives rise to brain waves, a useful signal for Brain-Computer Interfaces. When different parts of the brain are activated, localized and task-relevant, they give rise to characteristic electromagnetic field patterns that can be measured on the scalp with electroencephalography (EEG). These fields constitute an observable corollary of the underlying brain activity and are the analyzed signal in most BCI systems. EEG has been historically the most widely used methodology for BCI, partially owing to its excellent temporal resolution. Invasive methods, like single neuron recording in humans, are also compelling for BCI and have demonstrated superior performance in decoding experiments. The currently tiny prongs must increase in resolution before being used for non-research purposes. With progress, invasive methods might be a trump card for BCIs, especially as they enable reliable decoding of non-volitionally produced signals. There is a growing body of evidence highlighting that, while non-invasive techniques detect well-known rhythms, they are significantly impoverished in content. Additionally, there are findings suggesting that complex behaviour is not encoded in the superimposed rhythms [2].

TYPES OF BRAIN-COMPUTER INTERFACES

Brain-Computer Interface (BCI) technology is more broadly grouped into non-invasive and invasive BCIs. Invasive BCIs are surgically implanted devices within the brain that facilitate a connection between neural activity and an external machine. Essentially, an invasive BCI enables the direct extraction, transmission, and interpretation of data from an individual's brain with high spatiotemporal resolution. The most common form of invasive BCI utilizes micro- or macroelectrodes that can both record and deliver electrical impulses to the brain. Examples of invasive BCI devices include microelectrode arrays (MEA), screw-type electrodes, and fiberscopes. There are different types of MEAs, with some specifically designed for the deep brain. Other electrode types include subdural and depth electrodes, often used in stereo-electroencephalography (sEEG). Another common application of invasive BCI is Deep Brain Stimulation (DBS) therapy.

Invasive BCI provides a substantial benefit in terms of the signal quality obtained since the implants are near the neurons generating the signals. Furthermore, invasive BCI can provide signals outside the structure of the brain cortex, thereby enabling a broader spectrum of applications both within and outside the brain. However, invasive BCIs have a significant disadvantage in being that they require surgery, which always involves inherent risk. Some of the other limitations of modern-day invasive BCIs include signal-signal interference with other implantable devices and tensions-induced micro motion between the electrode and neurons, leading to reliability issues. On the other hand, non-invasive BCIs can read, analyze, and interpret neural commands through the skull and skin interface using a combination of electrical, neuroimaging, and chemical techniques. All non-invasive BCI measurements are acquired on top of the scalp using electrodes or sensors attached outside the body. EEG is the most common modality for non-invasive BCI. However, non-invasive BCIs can face challenges in terms of spatial resolution, sensitivity, and the presence of noise signals that can potentially cause ambiguity in signal interpretation [3].

Invasive BCIs

Invasive Brain–Computer Interface (BCI) technology is a sophisticated area of BCI research involving direct implantation in the brain. This kind of BCI records neural activity directly from the cortex using implanted electrodes or neuroprostheses. Since the electrical field generated by neurons can be recorded more effectively on the order of millimeters, invasive BCIs have a high spatial resolution compared to non-invasive ones. Their signal resolution and reliability are upper of a piece, making them accurate and safe for real-time data acquisition. It is worth noting that cortical neurons convert lot of data from dorsal on a predictive mode including movement type, speed or radius. Therefore, it is possible to accurately estimate these sorts about movement utilizing the sort of predictions based on implanted BCIs. This kind of information was refurbished to control a robotic arm, multi-joint arm, or hand.

"Invasive BCI devices are currently available in the comma of FDA approved neuroprostheses including brain computerized neurophysiology Neuro Port™ and Blackrock Microsystems™ allowing the times being in looking channels having each to recordings each neuronal unit whereas. Right has trended since these high-resolution signals data of devices. They may limit spread further to investigate supplemented LSCP properties of BCIs. Invasive BCIs on the broad probability used on the form interest of low their clinical in modernistic or the significant novel BCIs reading of one surgical potential of education BCI could be apparatus hospitals. For example, Device markets BCI robot could army soldiers, even if they were severely seduced in combat, see, hear or immovable locked-in status encoded see, hear or smells technologies need. On the other hand, developing BCI technologies is burdened the gentle functioning." On the scalp after wired of hidden censors there are risk to distribution of standard all kind of appropriate therapeutic and interest effects the construction sense of muscle and the asphyxial to permanently cut intracranial, hence, as promise contractions who must be directly inpatient therapy [4].

Non-Invasive BCIs

Brain-computer interfaces (BCIs) have recently received increasing attention with novel applications in diverse fields. Consequently, digital interaction with such devices would become essential skills, similarly, to using computers and smartphones nowadays. This paper provides an overview of BCI technology, digital skills and knowledge employed with BCIs, assumptions on the role of future digital literacy, and considerations when focusing on non-invasive BCIs. It is critical that BCI technology includes an understanding of hardware and software components, as well as knowledge about neuroscience principles and human brain functions. Neuroscientists and AI/machine learning specialists are the main professions associated with BCI research and development.

Most publications and patents in BCI research cater to an advanced audience because such technologies are cutting-edge. Non-invasive BCIs are more well-established and widely used than invasive BCIs, but their efficiency is too low for complex applications. They are likely to find their main applications in the gaming, education, and consumer electronic industries in the future. Despite the common interest in their research and a rapidly growing market, most people involved in those fields have little understanding of the technology behind BCIs or the skills required to develop them. Advanced signal processing skills could be further part of most – to make good use of BCI data and overcome limitations of signal acquisition methods. However, it is now possible to use BCIs and understand its critical issues without acquiring advanced knowledge of the underlying technology. Newly developed accessible tools and platforms allow almost everyone to start investigating and experimenting with BCIs. At the same time, significant academic efforts are being made to democratize BCI access among young students, artists, and enthusiasts – it is vital to outline ongoing innovations that might further reduce existing limitations for future users of non-invasive BCIs [5].

TECHNOLOGICAL COMPONENTS OF BCIs

The goal of brain–computer interfaces (BCIs) is to allow for communication between the brain and an external device. In typical BCI systems, brain signals from the scalp or directly from the cerebral cortex are acquired, processed, and analyzed to extract the user's intent. The intent is then classified and translated into commands that are used to control an external device. This in turn gives feedback to the user in a closed-loop system. The effectiveness and safety of this communication depend on the appropriate design and tight integration of the BCI components. There have been reviews of the technological aspects of BCI research, addressing the design and significance of the various components that make up a BCI system. This review not only discusses the current state of BCI technology but also presents and integrates the literature in the main technological challenges of BCIs. Furthermore, the review addresses important questions about BCI systems, such as the brain signals used and the effects of age on BCI systems.

Brain signal acquisition is the first step performed by BCI systems. These are picked up by various devices that transform brain signals into electrical, magnetic, or optical signals. The signals are typically rudimentary and many orders of magnitude weaker than the environmental noise, which can lead to measurement contamination. A paramount part of BCI systems is the signal processing that is used to convert raw brain signals into useful information regarding the user's intent. All brain signals and even some of their artifacts originating from biological or nonbiological sources are contamination (Fernando Nicolas-Alonso & Gomez-Gil, 2012) [1]. Amplifiers are used to increase the relatively weak signals from the brain. After amplification, the resulting signals may pass through analog filters, such as antialiasing filters in data acquisition devices. The amplified signal is digitized via an analog-to-digital converter, and software tools usually store the sampled data for subsequent offline or online computational analysis. The recorded brain signals are then pre-processed to combat artifacts or interferences that impair the interpretation of brain activity while keeping those components of interest. Generally, the data are further processed through artifact rejection by visual inspection or algorithms, adaptive filtering, and artefactual component translation. Following the data preprocessing is the feature extraction stage where useful discriminant information of the brain signals must be identified. This information consists of physiological and/or pathological changes present in the brain signals. The simplest and widely used features are the power spectral density (PSD) of the signals, which is the deterministic components of the energy distribution in the frequency domain. More advanced methods of signal analysis are also available [6].

Brain Signal Acquisition

Brain signal acquisition represents a fundamental stage in the development of a successful Brain-Computer Interface (BCI). The growing number of applications of BCIs has resulted in the concurrent development of various imaging, electrical, and optical techniques and devices aimed at capturing and interpreting neural signals from the brain. Commonly used approaches for non-invasive brain signal acquisition include electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), electromagnetic source imaging, near infrared spectroscopy (NIRS). Invasive brain signal acquisition methods include electrocorticography (ECoG) and intracortical microelectrode arrays (Fernando Nicolas-Alonso & Gomez-Gil, 2012) [1]. Non-invasive methods for endogenous brain signal acquisition, such as EEG and MEG have gained wider acceptance in the BCI community due to advances in noise reduction, the prevention and removal of artifacts and an increase in temporal and spatial resolution. MEG is an entirely non-invasive technique that measures changes in the magnetic fields generated by intracellular electric currents due to synaptic activity in the brain. fMRI is a non-invasive technique that acquires a stable blood oxygen level dependent (BOLD) signal with high registration of the source of neural activity. Intracortical microelectrode arrays and ECoG provide high spatial recording resolutions, since they both measure electrical potentials directly from the brain. ECoG is a semi-invasive method for long-term brain signal monitoring for epileptic patients that have been approved by the US Food and Drug Administration. Both invasive methods also provide the possibility of recording multi-unit activity instead of macroscopic signals (Portillo-Lara et al., 2021) [4]. The advantage of optical methods in neuroimaging is the high degree of spatial resolution that can be achieved. A main limitation common to all optical techniques is that photons are scattered and absorbed by biological tissues, such that the imaging resolution rapidly decreases with increasing depth in the tissue. The fNIRS method, however, provides portable and relatively cheap modules for imaging of the brain [7].

Signal Processing

Once the brain signals have been acquired from the subject through the EEG amplifier, the next step involves processing the brain signals (e.g., removing artifacts and noise, amplification of the useful information, filtering, etc.). This stage of the BCI is typically the domain for an algorithmic developer and the individual components of the BCI system might vary in complexity but would generally follow similar processes (Singh & Daly, 2014) [5].

Brain signals are typically masked by predominantly electrical noise (due to the electrodes, amplifier, motion of the subject, location of amplifier, etc.) so it is essential that an algorithm amplifies the useful information and appropriately filters the signals (e.g., such as band pass filtering done on the EEG amplifier or other filtering techniques to remove low frequency and high frequency noise). Additionally, processing is typically required before or after the EEG amplifier to improve the quality of the raw EEG signals (e.g., notch filtering done to remove power line noise). There are a variety of different mechanisms and techniques to process the acquired brain signals, including more sophisticated techniques to improve it further and a selection of these will be examined. Artifact removal (from the motor movements during the SPP task) can be difficult if not impossible, therefore, the artifact signal could be predicted and subtracted before any further processing occurs. Commonly, the brain signal is primarily in the 6–9 Hz band; therefore, the predictable artifact information could be situated in the <6 Hz band (this would also minimize the chance that the raw acquired artifact signal would correlate with the useful brain signals). Ensuring that a brain signal is consistently present within the EEG data is fundamental in obtaining and analyzing brain activity. To compare the online EEG data with EEG data, methods would have to be employed to inform IF the specific characteristics of a brain signal are present in the online data (this would typically be achieved with a calculating a feature vector from the EEG data and comparing it to a feature vector which was calculated from off-line EEG data). Since the BCI is processing the incoming EEG data in real-time, the algorithm(s) must act swiftly so that the BCI decides about the directional control in a timely manner (Latency: the time taken for the BCI system to provide the output after the appearance of a predicted brain signal in the online EEG). The algorithm(s) must also be designed to handle a stream of data lengths quickly (with respect to the duration of the data) to ensure a robust performance but this may be difficult if the online data is noisy and it is difficult to consistently identify a brain signal reliably (the duration of the online EEG data could also be too short to consistently identify the brain signal). Sometimes improving the quality of the incoming EEG data can help in achieving this; more recently, the use of machine learning algorithms has become popular in feature extraction and classification and is realistic for the concert. Machine learning algorithms that leverage and build on existing algorithms have also shown promising results. As this field advances workout, a doubt the application of more sophisticated machine learning techniques, such as artificial intelligence will result in a more accurate and robust performance. The challenge of realizing robust and accurate signal processing is by far the largest and most time-consuming task in the development process of any Brain Computer Interface. Successful detection of brain signals will allow individuals to fully harness their electrical brain signals for control, communication and rehabilitation applications. Any BCI system will involve a decoder which is tasked with converting brain data into control output, so essentially the brain produces electrical activity as actions or intentions change and this can be recorded and converted into the machinery (an Interface) to operate some other equipment or devices or control some other processes. Correspondingly, the detected brain signals may also be used to provide other direct feedback via the sensory system of the individual.

Feature Extraction and Classification

After the brain signals are acquired and pre-processed, feature extraction is the next step in BCIs. Feature extraction is the process of identifying important data from brain signals, which are subsequently used by a feature translation algorithm for BCI operation (Arbabi & Bagher Shamsollahi, 2017) [6]. It is a critical stage for BCIs and requires the extraction of the subject's intention or mental state from noisy, artefactual, and irrelevant background brain activity. A decision about which information is useful, and which information can be ignored is primarily made within the context of extraction tasks as features. The use of machine learning approaches is suggested to automate this process by training a system with effective features extracted via prior knowledge about the intended BCI task, in hopes of discovering hidden patterns which are hard to detect by conventional analysis.

Feature translation methods usually have a set of parameters whose values can greatly affect the final performance of the system. Also, initial feature representation requires pre-processing to filter and select important signal features. In this phase, a choice of numerous algorithms is available to research a solution to this problem: filtering and selection of relevant components. Thus, four different player roles are considered on this subject (Feature extraction and classification; filtering, selection, and classification; variable manipulation and algorithm; and processing representation and set of parameters), focusing on all aspects to produce an in-depth perspective. To produce the most informative feature value, an exploitation maximizes the representation of the given data. As a result, significant focus must be put on the initial processing of how the feature representation of the brain signals will be constructed as a good BCI feature vector. In the signal processing stage, extracted features need to be selected and must be provided to the classifier with proper format. Since a feature image contains a large amount of data, using all features cannot be meaningful because it is computationally intensive and can cause a harmful effect on classification accuracy [8].

Feedback Mechanisms

For all but the most trivial of applications, feedback mechanisms are likely to be necessary to guarantee that BCI systems are both effective and user-friendly. This topic of BCI research encompasses what information is fed back to the user, how, and when (Kosmyna & Lécuyer, 2017) [7]. A BCI is a closed loop between the user and the system. Here, the user interacts with the system, and the system gives feedback about its decision state after the user has interacted with the system. The BCI loop can be seen as captured in a box that is composed of the entire signal acquisition process, the signal processing, the feature extraction, and the classification, all controlled from a central unit. Related work distinguished between synchronous and asynchronous systems. In synchronous BCIs, there are pauses during the use of the system and no open-loop control. Another peculiar aspect of such BCIs is that information can enter the system through different modalities.

In most experiments and applications, the BCI provides information cued by the researcher. BCI user feedback has two major goals. First, feedback informs the user that the system has recognized the information that the user intended to convey. Second, feedback can inform the user about the correctness of the system's classification at each time step. This second type of feedback can be used by the user to refine calibration or control of the system. Providing timely and intuitive feedback is a key issue for BCI users. At first, subjects appreciate knowing what the BCI is detecting, but once they have achieved a certain level of proficiency and automation, they prefer that the system stays "invisible" unless a problem occurs. On the other hand, several works stress the role of conspicuous feedback to enhance BCI control or help users in understanding the setup. Several experiments show that a display that shows clearly how the system interpretations are obtained enhances user confidence in the BCI. Different approaches can be used to enhance user feedback, each providing a more engaging or intuitive interaction. These approaches are explored, and the design of systems providing different levels of feedback for each category is reviewed. Most BCIs aiming to maximize information transfer adopt paradigms in which the user is cued by the system and must wait to apply a mental strategy. However, BCIs based on self-paced control schemes have also been studied, allowing for the possibility of remaining "ready" while the system works in the background. This concept evolved from the scenario originally proposed as the regular operation of an asynchronous BCI system. Because the system offers feedback to the user, she initiates the task whenever she likes, and the system simply keeps providing responses in real-time. Nonetheless, more recent work also explored continuous feedback systems to foster interaction and ownership of the BCI application. Normally, the subject must repeatedly try a set of imagined movements until the system recognizes it. This results in an implicit association between the decoded brain patterns and the feedback characteristics of the attended movement. It has been observed that a similar task-tuning effect can be induced in online feedback by maintaining, over a certain period, a set of univariate EEG-biofeedback parameters between the user intention and the provided feedback. When subjects try to "learn" these arbitrary relationships, they become faster and more performant in subsequent online control. This positive effect of learned control-related brain feedback underscores the relevance of proper design of BCIs intended feedback. The concept of a BCIs application is particularly broad and encompasses areas as diverse as neuroscience, neuroimage, computer science, electrical engineering, signal processing, human-machine interfaces, and rehabilitative medicine. Such applications may differ in their feedback requirements according to the people using the devices and the context in which the interface is employed. Regarding feedback requirements, experimental BCI setups generally require more pronounced and customized user feedback, since subjects have little a priori knowledge of the association between signal modulation that can induce control and the system feedback. Iterations of adapted feedback within experimental sessions have been shown to improve BCI control or boost communication throughput. Developed BCI applications predominantly use systems that naturally include feedback, such as game-based applications, augmented communication devices, or rehabilitation aids. In this guideline, an attempt is made to cover a broad spectrum of acoustic, visual, and tactile feedback approaches, focusing on the design principles, and human factors. Biofeedback paradigms consist of providing the user with real-time feedback about the brain activity, which can be used to improve brain function or behavior. In a BCI context, biofeedback can have several meanings, one of which refers to the on-line feedback of the user to decode the intended task.

APPLICATIONS OF BCIs

Applications of Brain-Computer Interfaces (BCIs) can be categorized into four broad areas: Medical BCI; BCIs for assistive technologies; BCI application for neurorehabilitation; and BCIs in gaming. BCIs have made remarkable progress over the last few years in different directions. Steady technological advances are mostly driven by the necessity to improve user-friendliness, to increase BCI speed and accuracy, and to make BCIs affordable for those in the need of them. Additionally, to these technological advances, the last few years have also seen a significant increase in the number of research and development projects addressing issues related to BCI application and their potential niche in the vast user-assistive technology grid. These latter projects are of utmost importance as BCIs are not stand-alone devices and will only make a difference to the life of disabled people if they can be integrated into the context of their everyday use.

Firstly, the medical application of BCI mainly refers to using BCIs for neuroprosthetics, or communication aids for “locked-in” patients or patients with disorders of consciousness (DoC). For instance, BCI devices in the form of a neuroprosthetic implant based on ECoG electrodes are a promising approach for the restoration of motor control capability. Secondly, BCIs can be employed as assistive technologies for controlling a wide range of external devices. The fundamental principle behind any BCI system is to directly translate brain activity into features for control. Thirdly, the application of BCIs for assistive and therapeutic purposes in rehabilitation centers could greatly facilitate neurorehabilitation protocols post-stroke or after a traumatic brain injury. It was shown that personnel require little additional training to learn how to set up subjects and obtain extensive neural activity from each patient. Lastly, there has been a growing interest in the gaming sector to explore how BCIs can be integrated into entertainment systems and how to offer innovative, immersive technologies to the users’ overall experience. Some success stories in the above-mentioned four areas of BCI applications and some ongoing projects that aim to sustain and extend these applications will be reviewed as expanding further [9].

Medical Applications

Research and development in Brain-Computer Interfaces (BCI) have made encouraging progress in recent decades, driven by advances in various engineering disciplines and neuroscientific techniques. BCI applications are typically categorized in accordance with the users or areas of deployment; and BCIs have found applications in fields, such as military, security, gaming, and entertainment. Nonetheless, because of the direct and essential relevance to the improvement and preservation of human well-being and quality of life, the medical applications of BCIs are among the most significant, impactful, and justifiably well-funded areas of BCI research, development, and translation. The ongoing research activities, translational efforts, and technological advances in this area of BCIs are varied, multifaceted, and often take advantage of preconditioned interfaces between brain and environment.

Assistive Technologies

The last few years have witnessed rapid advancements on the front of non-invasive brain signal analysis and in hardware development. Brain-Computer Interfaces (BCIs) are about to revolutionize the classical approach to inputs/outputs conventional interfaces have, such as computer mice or keyboards. They allow to overcome the communication interface that links human brain to any other device. Therefore, BCIs can be seen to make neurophysiological signals a bidirectional communication channel, a shift of paradigm in respect to traditional approaches to neuroscientific technology. These neurophysiological signals are extracted non-invasively from the brain using electrodes and parametrize the ongoing electric activity. The field of BCIs is highly interdisciplinary, and joint efforts of neural engineers, computer scientists, and medical researchers are crucial when attempting to design a device which could be employed to enable communication and control in severely disabled people. This work represents the prototype of a system providing the user with environmental information on the transformed signals and, similarly, representing the EEG signals neuronal origin. This represents the general framework for a BCI and its applications among an Urban Ambient Intelligence and Universal Human Computer Interface. Furthermore, models for the estimation of the visual evoked potentials and principal components of the EEG sources analysis are outlined. Perspectives on future human-machine interface systems based on the described results show an overall interest [10].

Neurorehabilitation

Broadly defined, neurorehabilitation is the process of assisting recovery from injuries to the nervous system. It is a rapidly evolving and promising application of Brain-Computer Interfaces (BCIs). BCIs are widely adopted to assist in brain injury rehabilitation, finding utility in scenarios ranging from acute care to remote assistance months after injury. They are utilized in various traditional and innovative therapy schemes in concert with expert therapists including stroke and traumatic brain injury recovery programs. BCI-augmented therapy aims either to stimulate neural activity and enhance neuroplastic changes or to immediately engage patients by providing contingent feedback on desired neural behavior. Neuroplasticity is the brain’s ability to reorganize itself by forming new neural connections in response to learning or experience. Brain-computer interface (BCI)-assisted therapies aim either to stimulate neural activity and promote neuroplastic changes conducive to recovery or to engage patients in rehabilitation exercises by providing contingent feedback on evolving neural activity. Such BCIs apply a range of different intervention strategies, including electrical stimulation, motor-imagery (MI) training, and monitoring natural movements. Therapy-based intervention, coupled with a real-time BCI, are proposed to restore the affected limb’s various control functions. The control of the affected limb is developed from rudimentary modes, which provide motivation and create some movements. Also explored is the role that plasticity underlying learning-like features of patient brain activity might play in enabling patients to successfully operate a BCI and the BCI rehabilitative effects in general. BCI in combination with a physiotherapy device for elbow training with poststroke patients. Custom-made BCI-controlled electrical stimulation for hand restoration after stroke is investigated in 19 chronic poststroke patients. An EEG-based BCI was developed to detect individual movement segments during a grasp-and-lift task. A noninvasive BCI-controlled hand orthosis was developed to assist hand closing in chronic stroke patients. Participants showed improvements in grasp strength, tenodesis, reaction time, muscle tone. Development and evaluation of a novel BCI in combination with a physiotherapy setup have proposed novel solutions and strategies for the brain control of challenging robotic assistance tasks. BCI also demonstrated a reduction of ataxia, severity level in cerebellar stroke survivors [11].

Gaming and Entertainment

No longer tied to animal training, researchers and engineers are augmenting current applications and developing entirely new landscapes of Brain-Computer Interface (BCI) uses. Gaming is described as one of these newer BCI applications; it is followed by a predictive analysis of challenges and unlikely convergent paths including the use of fog-harvesting technologies, a return to animal empathy studies, and brain-controlled indie-rock bands which use Electric Fish and Dalek choreography. The gaming industry is a rapidly evolving and advancing market which, in 2014, was worth an estimated $81.5 billion market in the world. It is a market that is always looking for the next new feature or gimmick:

previously VR, mobile ports, or motion controls have been featured novelties. Gaming combined with BCI could be the next frontier in this innovation. Early in 2000, BCI games were developed using rather simple settings, were not marketed on the commercial level, and were very rudimentary regarding gameplay and graphics. For the most part it was intended to be an experiment to see if BCI could be used in the entertainment industry. However, in the past couple of years gaming companies are increasingly experimenting or integrating this technology into their consoles and platforms. There is even a new generation of gaming developed that works dependently with BCIs, such as the Void, Project Epoc, Project Vienna, and PlayStation mind skin [12].

CHALLENGES AND LIMITATIONS IN BCI RESEARCH

Introduction

Since the first demonstration of successful electroencephalogram (EEG) control of a computer cursor in 1977, the development of Brain-Computer Interface (BCI) technology has been ongoing for over four decades. In recent years, there has been a proliferation of research on BCIs. This new technology has shown potential in augmentative and alternative communication (AAC) applications for people with neurological impairments. This type of BCI system enables users to communicate using non-muscular strips, thereby providing a new communication option to people who cannot control their muscles. The system can also be used as a practical communication assistive device for people with severe neuromuscular impairments, such as amyotrophic lateral sclerosis (ALS).

Although numerous studies have demonstrated the feasibility of designing BCIs to perform various tasks, there are several challenging problems that must be addressed if the technology is to be practically useful beyond the laboratory. An assessment of these challenges is generally lacking in the published BCI literature, and there has been little public discussion of some important issues. This paper takes a comprehensive view of the field and raises various concerns regarding both the current state of the art and the near- and long-term future of BCI research and development.

ETHICAL AND PRIVACY CONSIDERATIONS IN BCI DEVELOPMENT

As BCI's further develop and brain data tend to be more easily accessed, it is crucial to take the necessary steps to assure that safeguards are in place to prevent misuse as well as agreeing to guidelines of good practice. The most fundamental aspect of any technology is the control that an operation has over it and the potential choices in which it is used. When the technology is invasive, this notion becomes more crucial as the invasive BCI device directly influences the brain and can pose irreversible effects should things go wrong. Issues pertaining to consent, autonomy and potential dual use are brought to the forefront of these dilemmas. Data privacy concerns over the information being collected, how it is being collected, who it is being collected by, where it is being stored, and for what the data is going to be used emerge as paramount. Compliance to FAT* or privacy preserving methods is urgent, mandating the production of a thorough audit trail that could be regularly checked. Otherwise, the appeal is for a greater recognition and an amplification of the importance placed on data concerning the concept, genesis of a decision or intention, or any form of brain-generated text. Regulation of intent decoding is petitioned for. Paranoia must be set aside when it arises exclusively from the outside view of mental commands but is not intended as such. It is better for policymakers, BCI operators, or even bystanders to remain vocal about what form of intent decoding is performed unless it is forbidden. Transparency and accountability need to be at the epicenter of every action taken during deployment, demonstration, promotion, or development to build trust. Furthermore, the goal should have an unbiased effect on the societal dynamics of implementing BCI funded research. Accessibility is entry-level with issues concerning ageing, disability, or geographical considerations. There are calls for putting into place guidelines structured on good research practices, in combination with ethical frameworks. All these improvements need to focus on equality of treatment between potential beneficiaries, and distribution of responsibilities among stakeholders [13].

RESULTS AND DISCUSSION

Results

The field of Brain-Computer Interfaces (BCIs) has made significant advancements in recent years, with several notable successes in both clinical and research settings. Non-invasive BCI technologies, such as Electroencephalography (EEG), have demonstrated the ability to decode neural signals and allow users to control external devices, including prosthetics, computers, and robotic systems. Recent studies have shown promising outcomes in the rehabilitation of motor disabilities, such as enabling stroke patients to regain some control over limb movements through motor imagery tasks. Additionally, non-invasive approaches have been used to develop communication systems for individuals with severe disabilities, allowing them to express thoughts through virtual keyboards or speech synthesis software.

In terms of cognitive enhancement, BCIs have been explored in applications like improving attention, memory, and learning through brainwave modulation. Furthermore, advancements in signal processing techniques, such as machine learning algorithms, have improved the accuracy and reliability of BCIs, leading to faster response times and better adaptation to individual user needs.

DISCUSSION

Despite the promising outcomes, several challenges remain in the development and widespread adoption of BCIs. One of the primary obstacles is the issue of signal quality and reliability. While non-invasive methods, like EEG, are more accessible, they often suffer from lower resolution compared to invasive techniques, leading to challenges in accurate signal acquisition. Moreover, noise interference from both external and physiological sources can significantly reduce the performance of BCI systems.

The training of users to effectively operate BCIs also remains a significant barrier. To achieve seamless communication or control, users must often undergo extensive training, which can be time-consuming and mentally exhausting. As a result, systems that require less user effort to adapt and learn are crucial to ensure broader adoption, especially in clinical settings where patients may not have the cognitive or physical capacity for long-term training.

Another critical issue is the ethical implications of BCIs. The ability to decode and interpret thoughts raises concerns about privacy, security, and the potential for misuse. As BCI systems evolve to become more sophisticated, there is an increasing need for regulations and safeguards to protect users' mental privacy and ensure that these technologies are used responsibly. Additionally, there is the risk of unequal access to such technologies, which could exacerbate existing social inequalities.

Looking ahead, the future of BCI research is focused on overcoming these limitations. Innovations in signal processing, such as the use of deep learning techniques, are enhancing the decoding of brain activity with greater precision. Additionally, the development of more comfortable and user-friendly interfaces, including wearable devices and non-invasive neurostimulation methods, is making BCIs more accessible for a wider range of applications. On the horizon, hybrid BCIs combining both invasive and non-invasive approaches could provide a balance of high performance and user convenience.

In conclusion, while BCIs have made impressive strides, there is still much work to be done to enhance their functionality, usability, and ethical deployment. As research continues, the integration of BCIs into everyday life holds vast potential for enhancing human abilities, enabling new forms of communication, and providing solutions for individuals with neurological disorders. However, it will be crucial to address the technical, social, and ethical challenges to ensure that BCIs benefit society.

FUTURE DIRECTIONS AND EMERGING TRENDS IN BCI TECHNOLOGY

The field of Brain-Computer Interfaces (BCIs) has seen impressive growth in recent years, partly due to advancements in signal processing algorithms, along with improvements in the quality of data acquisition hardware. As a result, the efficiency, performance, and functionality of BCIs have increased significantly. Besides the operations of BCI, there are several other research directions aimed to enhance or expand the functionality of BCIs. Such a direction of research has been pursued by various research groups aiming to build adaptive BCIs, which would automatically optimize BCI performance to each individual user based on adaptive signal processing and machine learning algorithms. The potential breakthrough and transformative trend in BCI development may come with the integration of BCIs with artificial intelligence (AI) and machine learning that will improve the accuracy and speed of signal interpretation in designing BCI systems capable of robust operation in dynamically changing environments or allow for seamless transition between different BCI paradigms. These trends aim for the development of lightweight, portable, and easy to maintain BCI systems that could be integrated into ubiquitous electronic devices and further increase the range of potential BCI applications. Promising progress has been made in the miniaturization of BCI components and the use of new materials that would bring a huge breakthrough in creating more user-friendly BCI devices.

Aside from the widely researched BCI types, there is also the growing interest in other types of BCIs, including tactile BCIs which are investigated, combining the advantages of auditory and vibratory stimulations, provided concurrently or in alternation, could effectively modulate neural activity in a manner that could be used to implement tactile BCIs. In the coming decades, BCI systems may become an entirely new branch in the rapidly evolving field of Information and Communication Technologies (ICT), influencing various aspects of human life just like smartphones, the internet, and other recent technological revolutions. Besides the wide expansion of BCI application in enriching cognitive-affective brain states, within the next 20–30 years, these technologies could change the way the human cognitive system functions and reshapes the human perceptions, consciousness, and self-reflection. At the same time, BCIs might be a powerful platform for embracing the knowledge and theories formulated by various scientific disciplines into a universal and comprehensive understanding of the human brain and its functioning.

CONCLUSIONS

Brain-Computer Interfaces (BCIs) have rapidly evolved from theoretical concepts to practical technologies with transformative potential across various domains, including healthcare, communication, and human-computer interaction. This paper has explored the fundamental principles of BCIs, their applications, and the technological advancements driving their development. From assisting individuals with disabilities to providing new forms of human augmentation, BCIs promise significant improvements in quality of life and human potential.

However, despite the progress made, several challenges remain. These include technical limitations, such as signal accuracy and reliability, as well as ethical concerns related to privacy, security, and the implications of direct brain interaction. Addressing these challenges will require continued innovation, interdisciplinary collaboration, and careful regulatory oversight.

Looking forward, the future of BCIs appears promising, with potential breakthroughs in neural decoding algorithms, non-invasive interfaces, and integration with AI technologies. As BCIs become more efficient and accessible, they will likely open new frontiers in neuroscience, rehabilitation, and even cognitive enhancement. Ultimately, BCIs have the potential to redefine the relationship between humans and machines, offering a new paradigm for interaction and communication.

REFERENCES

1. Fernando Nicolas-Alonso L, Gomez-Gil J. Brain Computer Interfaces, a Review [Internet]. 2012 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.
2. Peksa J, Mamchur D. State-of-the-Art on Brain-Computer Interface Technology [Internet]. 2023 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.
3. Zhao ZP, Nie C, Jiang CT, Cao SH, Tian KX, Yu S, et al. Modulating Brain Activity with Invasive Brain–Computer Interface: A Narrative Review [Internet]. 2023 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.
4. Portillo-Lara R, Tahirbegi B, Chapman CAR, Goding JA, Green RA. Mind the gap: State-of-the-art technologies and applications for EEG-based brain–computer interfaces [Internet]. 2021 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.
5. Singh H, Daly I. Translational Algorithms: The Heart of a Brain Computer Interface [PDF]. 2014.

6. Arbabi E, Bagher Shamsollahi M. Evaluation of Classical Features and Classifiers in Brain-Computer Interface Tasks [PDF]. 2017.
7. Kosmyna N, Lécuyer A. Designing Guiding Systems for Brain-Computer Interfaces [Internet]. 2017 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.
8. Alkawadri R. Brain–Computer Interface (BCI) Applications in Mapping of Epileptic Brain Networks Based on Intracranial-EEG: An Update [Internet]. 2019 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.
9. Millán JR, Rupp R, Müller-Putz GR, Murray-Smith R, Giugliemma C, Tangermann M, et al. Combining Brain–Computer Interfaces and Assistive Technologies: State-of-the-Art and Challenges [Internet]. 2010 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.
10. Shih JJ, Krusienski DJ, Wolpaw JR. Brain-Computer Interfaces in Medicine [PDF]. 2012.
11. Yang S, Li R, Li H, Xu K, Shi Y, Wang Q, et al. Exploring the Use of Brain-Computer Interfaces in Stroke Neurorehabilitation [Internet]. 2021 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.
12. Chen Y, Wang F, Li T, Zhao L, Gong A, Nan W, et al. Several inaccurate or erroneous conceptions and misleading propaganda about brain-computer interfaces [Internet]. 2024 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.
13. Livanis E, Voultsos P, Vadikolias K, Pantazakos P, Tsaroucha A. Understanding the Ethical Issues of Brain-Computer Interfaces (BCIs): A Blessing or the Beginning of a Dystopian Future? [Internet]. 2024 [cited 2025 May 21]. Available from: https://www.ncbi.nlm.nih.gov.

