Review Article

A Comprehensive Survey of Brain–Computer Interface Technology in Health care: Research Perspectives

Abstract

The brain-computer interface (BCI) technology has emerged as a groundbreaking innovation with profound implications across diverse domains, particularly in health care. By establishing a direct communication pathway between the human brain and external devices, BCI systems offer unprecedented opportunities for diagnosis, treatment, and rehabilitation, thereby reshaping the landscape of medical practice. However, despite its immense potential, the widespread adoption of BCI technology in clinical settings faces several challenges. These include the need for robust signal acquisition and processing techniques and optimizing user training and adaptation. Overcoming these challenges is crucial to unleashing the complete potential of BCI technology in health care and realizing its promise of personalized, patient-centric care. This review work underscores the transformative potential of BCI technology in revolutionizing medical practice. This paper offers a comprehensive analysis of medical-oriented BCI applications by exploring the various uses of BCI technology and its potential to transform patient care.

Keywords: *Alzheimer, brain-computer interface, human-computer interaction, neurofeedback, prosthetic control*

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Introduction

The brain–computer interface (BCI) technology has emerged as a pioneering innovation with profound implications across various domains, particularly in the realm of health care. By bridging the gap between the human brain and external devices, BCI systems offer innovative solutions for diagnosis, treatment, and rehabilitation, thereby transforming the landscape of medical practice. BCI holds significant importance and has made substantial impacts across multiple fields, particularly in recent years. BCI technology has revolutionized numerous domains across various fields by facilitating direct communication between the human brain and external devices.[1] Especially in health care, BCI has transformed diagnostics, treatment, and rehabilitation processes, offering personalized and targeted solutions for patients with neurological conditions and physical disabilities.[2] Furthermore, numerous other applications are found in fields such as gaming, education, and human-computer interaction (HCI), enhancing user experiences and fostering innovation.

In this review paper, we present an extensive analysis of BCI applications, with a primary focus on its pivotal role in medical settings. Through this comprehensive analysis of relevant research papers, we aim to explore the diverse applications of BCI technology and its potential to revolutionize patient care. Moreover, BCI applications in medical practice are further segmented into distinct categories, facilitating a systematic exploration of its multifaceted impacts on the healthcare industry. The taxonomy adopted in this paper includes Accessibility, General Medical Applications, Psychology/Neurology, Pediatric Applications, and Personalized Medicine.

For this review work, PubMed was selected as the primary database due to its extensive collection of biomedical and life sciences literature, which is highly relevant to medical applications of BCI technology. By leveraging PubMed, the study ensures access to peer-reviewed articles pertinent

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to BCI and multimodal emotion recognition in healthcare contexts. Supplementary databases such as Scopus, Web of Science, and IEEE Xplore were considered to broaden the scope, integrating perspectives from allied health and engineering. The literature review covered studies published from 2014 to 2024, capturing advancements in BCI and emotion recognition over the past decade. This timeframe was chosen to include the most recent developments in the field while allowing historical context to be considered.

The taxonomy is presented in Figure 1, including the number of papers reviewed in each section. The taxonomy outlines the distribution of reviewed papers across five major categories, with each category thoroughly explored. As illustrated in Figure 2, it ensures a comprehensive examination of the medical applications of BCI technology. The systematic review process employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) model, which is pivotal for ensuring transparency and reproducibility in research.[3] This model was chosen for its structured framework that enhances the clarity and comprehensiveness of systematic reviews. The significance of the PRISMA model lies in its ability to guide researchers through each stage of the review process, from protocol development to reporting, thus minimizing bias and improving the overall quality of evidence synthesis.[4] Following the PRISMA method, this taxonomy initially involved collecting 300 papers covering different BCI applications. From this pool, we refined our focus to 220 papers specifically related to BCI in medical applications. Notably, this process involved filtering out combined applications beyond the medical scope, focusing solely on medical applications, both invasive and noninvasive. Some examples of searching methods or strategies using keywords and Boolean phrases in PubMed are as follows: "Multimodal emotion recognition," "brain–computer interface," "EEG emotion recognition," "machine learning" "Prosthetic control," "brain–computer interface applications." These search terms ensured the retrieval of articles spanning the interdisciplinary approaches necessary for studying BCI applications in health care.

Brain–computer Interface System

The human brain is referred to as the most sophisticated organ, captivating the curiosity of researchers, scholars, and engineers for centuries. The capabilities and intricacies of the human brain is a fascinating and interesting source of exploration, pushing the boundaries of technology and neuroscience. One of the most notable achievements in this area is the development of the BCI system, which builds a remarkable connection between the human brain and computers or machines. BCI system represents an advanced merging of computer science, neuroscience and engineering while offering the potential scopes to interact with the human brain or mindset with technology. This technique

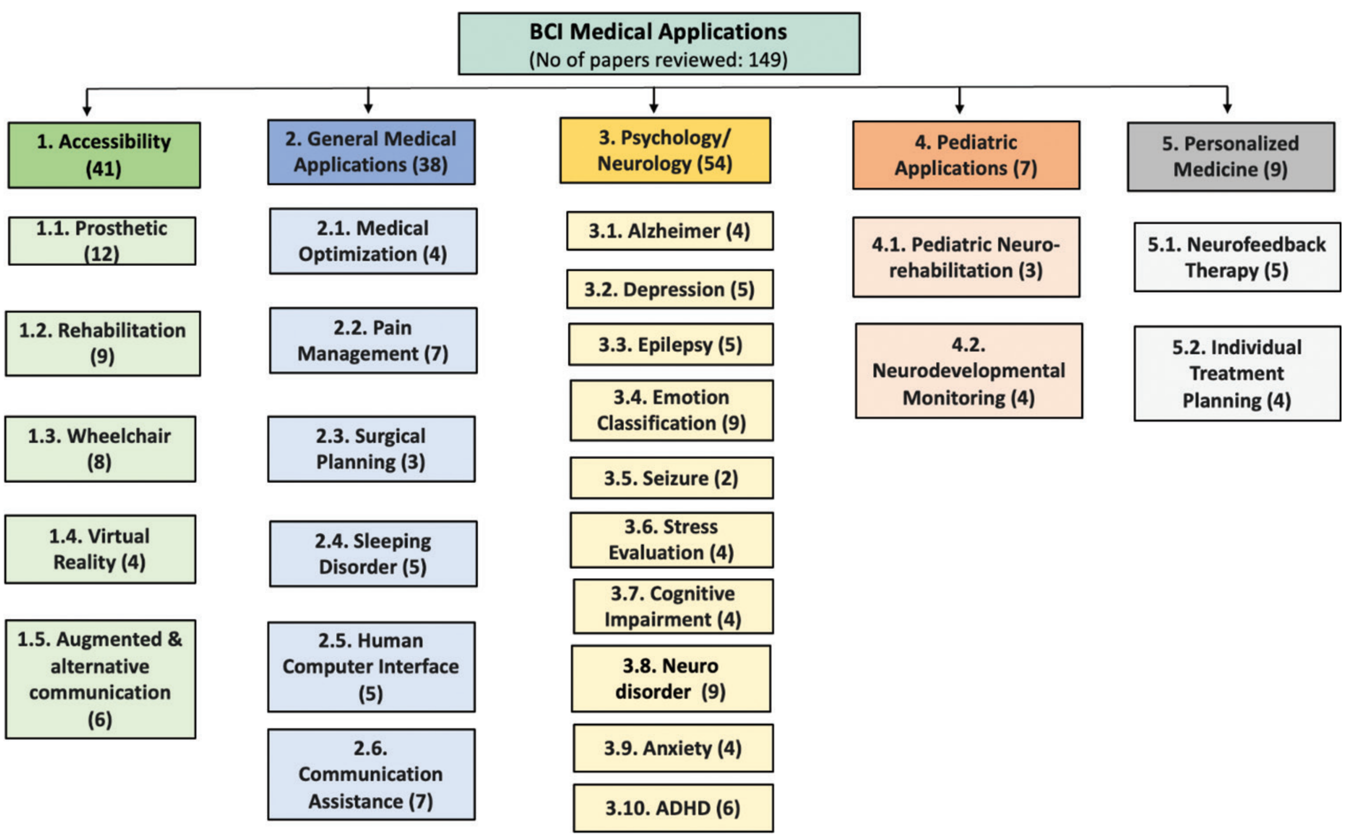

Figure 1: Brain-computer interface medical application taxonomy

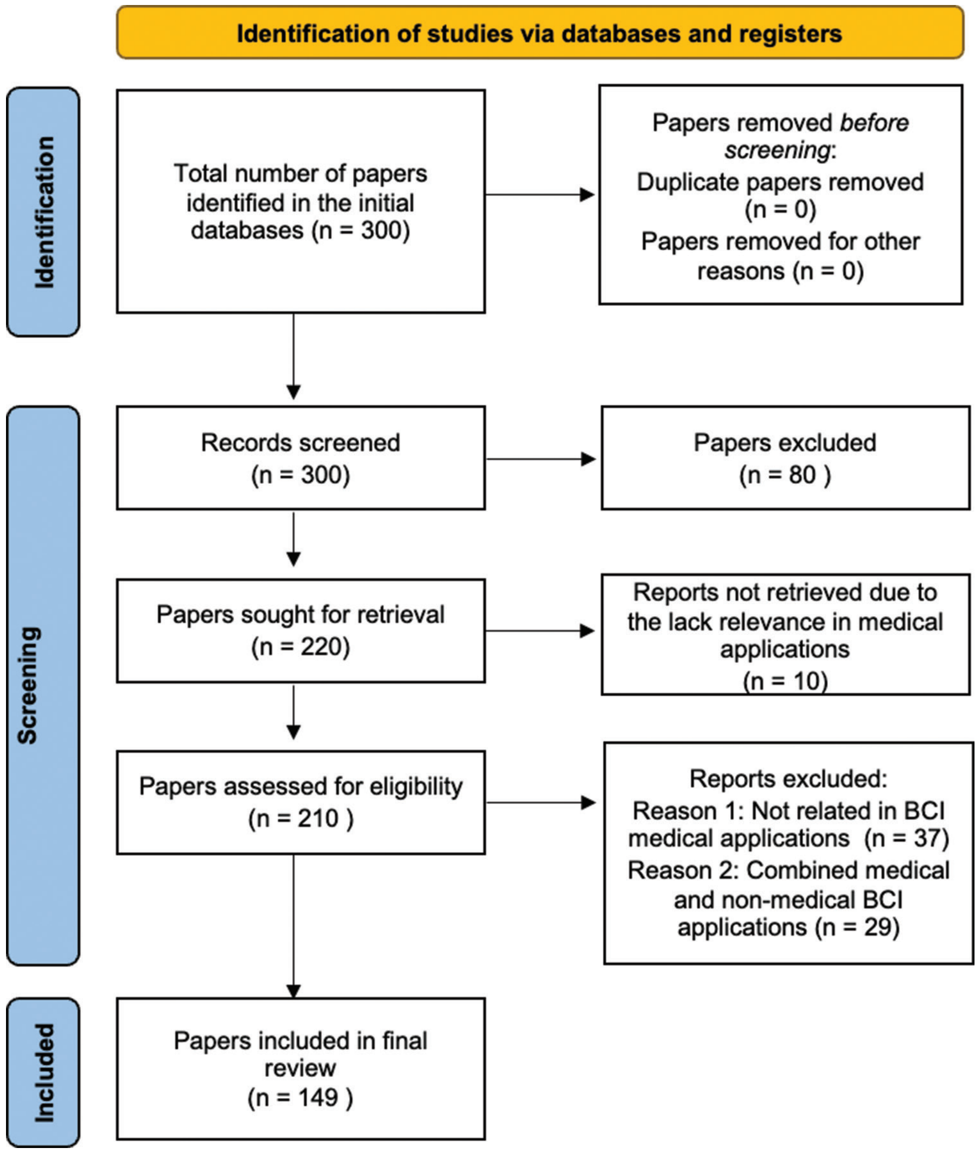

Figure 2: PRISMA flow diagram for systematic review approach

empowers individuals with several disabilities, such as lost motor functionalities and paralysis

At its core, BCI technology is sophisticatedly connected with capturing and interpreting psychological signals, such as electroencephalogram (EEG). These signals serve as a gateway to unlock the remarkable potential of establishing a direct connection between the human mind and external devices. BCI leverages the electrical activities generated by the brain (EEG) while decoding emotions, thoughts, and intentions and translating the signals into meaningful instructions for machines, computers, and prosthetic devices. It is crucial to explore the relationship between the physiological signals and technology interfaces to understand the extraordinary capabilities of the advancement of BCI systems. The overall process of integrating the BCI system for medical sector application with EEG signals is illustrated in Figure 3.

Integration of brain–computer interface system with physiological signals EEG for medical applications

The process of integrating BCI technology with psychological signals can be outlined as follows:

A. Signal acquisition: This process begins with the signal acquisition from EEG or ECG experiment from the electrodes placed on the scalp (for EEG). The electrical activities of the brain and heart are represented by the signals[5,6]
B. Preprocessing: The extracted signals are then preprocessed to remove artifacts, noise, and any unwanted interferences.[7] This is a crucial step that ensures that the data is clean enough and suitable for further analysis
C. Extracting features: Relevant, significant features, including amplitude value, components, frequency, or other key characteristics, are later extracted from these preprocessed signals, which carry insightful information

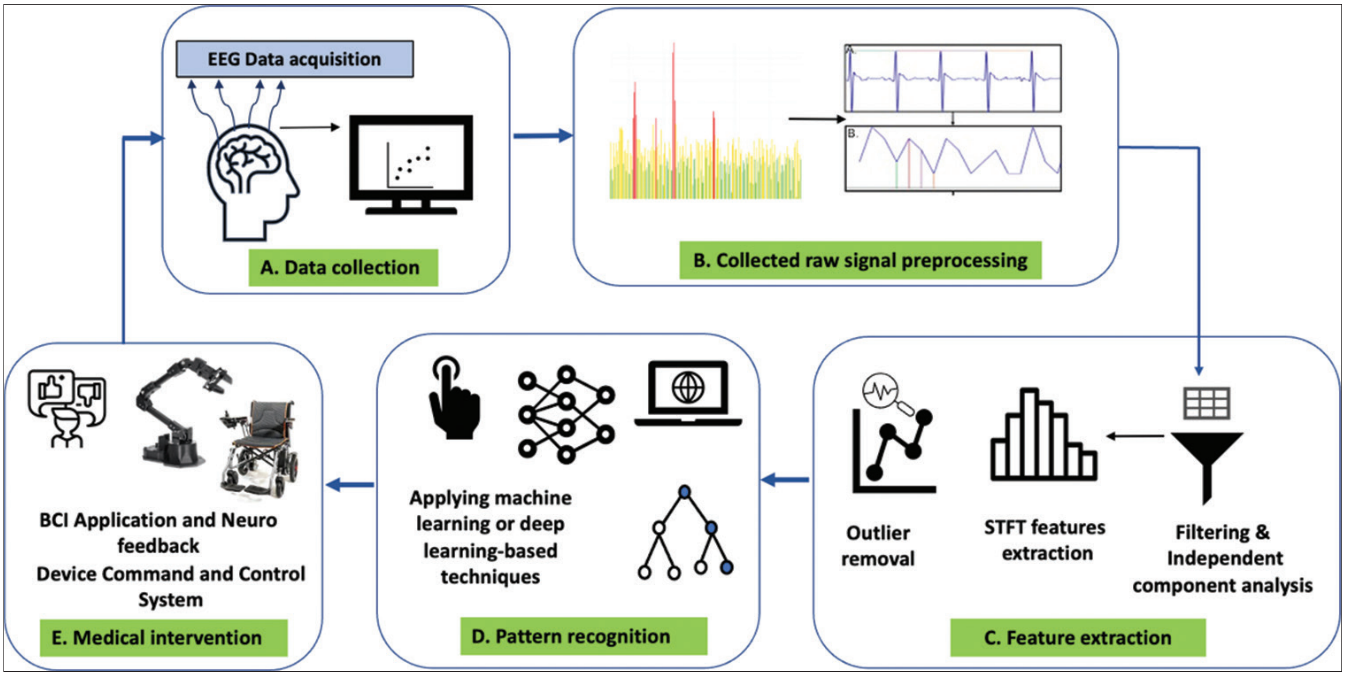

Figure 3: End to end brain-computer interface system for medical intervention

about the users' condition or state[8]

D. Recognizing patterns: Machine learning, deep learning algorithms, or other pattern recognition techniques are employed to analyze the extracted features. These algorithms undergo training to identify and recognize signatures or patterns within the data that correspond to physiological or mental states[9]

E. Medical intervention: The BCI system makes determinations based on the patterns related to the user's intentions or states.[10] As an illustration, it can determine whether the user wants to manipulate a cursor on a particular screen or initiate a command.

   a. Controlling command generation: The BCI system converts the decision into a control command for an external application or device. Such command generation encompasses a wide range of potential actions, such as controlling robotic arms, computer cursors, wheelchairs, or any other devices or software that users intend to interact with
   b. External device's output: The generated control commands are transmitted to the external devices or applications, which subsequently carry out the desired actions or responses to the user's intent
   c. End: The BCI system continues looping through these stages, allowing real-time interaction between users and external devices/applications. The process operates continuously and adaptively, with the BCI system constantly updating its understanding of the user's intentions.

Applications of Brain–computer Interface

The scope and applications of BCI are versatile within and beyond the medical sphere. In the medical realm, it has been providing hope and transformative remedies for individuals with profound disabilities, facilitating the regain of both mobility and communication skills. BCI systems are playing promising roles in assisting patients in recovering from neurological diseases and ailments.[11] There are numerous research works where scholars have worked on developing such systems. To gain deeper insights and understanding into the breadth of this research, it can be categorized into distinct taxonomies or segments.

BCI medical applications are diverse and promising, ranging from advancing mobility to enhancing patient accessibility. Numerous transformative solutions can improve the lives of numerous patients facing many complicated health issues.[12] From the perspective of modern real-world applications, BCI technology has demonstrated immense significance in assistive technology while providing support to people with disabilities. BCI-controlled prosthetic devices, such as exoskeletons and limbs, enable the disabled to regain their motor functions and independence. Moreover, neuroplasticity and motor learning are other ground-breaking methods that provide real-time feedback to patients with spinal cord injuries, stroke, and other neurological conditions. The modern applications of such technology in medical domains are diverse, and this medical application domain can be further thoughtfully divided into distinct categories to comprehend the vast scope and significance better. The categories include "Accessibility," which encompasses prosthetic control, rehabilitation, and wheelchair mobility solutions; "General Medical Applications," which extends to communication support and neurological condition management; and "Psychology/Neurology," which delves into areas such as Alzheimer's disease detection, depression assessment, emotion classification, epilepsy monitoring, and stress evaluation. Each of these segments plays an important role in harnessing the potential of BCI technology to enhance healthcare outcomes, from restoring mobility and communication abilities to advancing our understanding of complex neurological and psychological conditions.[13]

Accessibility

The objective of such studies is to research BCIs on patients suffering from amyotrophic lateral sclerosis (ALS), brain stroke, brain/spinal cord injury (SCI), cerebral palsy, muscular dystrophy, and so forth. BCI accessibility applications represent a revolutionary advancement while improving the lives of individuals with physical limitations and communication challenges.[14] One specific application in this regard is showcased by Manyakov *et al*.[15] where noninvasive BCIs are used based on electroencephalograms (EEG) recorded on the subject's scalp, requiring no surgical procedure. The event-related potentials (ERPs) that were the focus of this study were electrophysiological responses to an internal or external stimulus using the P300 BCI response. The study was conducted using the prototype of a miniature EEG recording device that communicates wirelessly with a USB stick receiver. This accessibility domain can be further segmented into prosthetic control, rehabilitation, and wheelchair mobility solutions.

Prosthetic control

There are various techniques for controlling a prosthetic hand, including a shoulder harness, myo-electric control, and the WILMER elbow. A shoulder harness requires movement of the upper arm or shoulder, while myoelectric control requires some nerves or muscle activity in the amputated extremity.[16] The WILMER elbow uses elbow motion to control the hand. However, these systems are not useful for patients with total paralysis, but an EEG-based BCI provides a new control channel for individuals with severe motor impairments. This involves detecting motor actions from the EEG to control an externally powered prosthesis device during grasping. The BCI can be controlled by a binary output signal obtained through the classification of EEG patterns during hand movement imagination. Utilizing oscillatory EEG components as input signals for a BCI necessitates real-time analysis of EEG signals.

Guger *et al*.[17] combined recent BCI developments with modern prosthetic tools. The BCI experiment involved the use of EEG to control a prosthesis through binary output signals, obtained by classifying EEG patterns during imagination of left- and right-hand movements. The EEG setup consisted of a minimum of two electrodes, positioned close to primary hand areas (C3 and C4), to capture oscillatory EEG components as input signals for the BCI. In another study, Miranda *et al*.[18] used Blackrock Microsystems NeuroPort data acquisition system for recording prosthetic data. It was also used in converting neural firing rates into functional mapping. For the prosthetic limb commands in endpoint velocity space, mathematical models were integrated into BCI systems to restore and/or facilitate near-natural neural and behavioral functions to advance neural decoder capabilities through multi-scale, dynamic models for the brain's plastic changes.

Furthermore, Katyal *et al*.[19] developed a method for collaborating with the BCI approach for the autonomous control of a prosthetic limb system, enabling amputees to achieve more natural, efficient, and intuitive control of their prosthetic limbs. The project proposes a BCI system that uses a combination of electroencephalography (EEG) and electromyography (EMG) signals to facilitate the control of a prosthetic limb. The system uses a deep neural network to classify and interpret the EEG and EMG signals, which are then used to control the prosthetic limb in real-time. Similarly, Laiwalla *et al*.[20] proposed a distributed wireless network of sub-mm cortical microstimulators for BCIs. This system aims to enhance the functionality and performance of BCIs by enabling precise and targeted neural stimulation, thereby improving the control and feedback provided to the user.

In another study, Chapin *et al*.[21] used a linear decoder to map the recorded neural activity to the desired movement of the robotic arm in real-time. The decoding algorithm was implemented in MATLAB software and incorporated a Kalman filter to estimate the state of the arm and correct for errors in the decoding process. The authors report high accuracy and low latency of the neural interface in controlling the robotic arm. The study suggests the potential of the proposed neural interface for the development of advanced prosthetics for individuals with motor disabilities. Again, Oppus *et al*.[22] described the design and development of a 3D-printed prosthetic hand that incorporates sensors for BCI control and a voice recognition module for voice commands. The authors reported successful testing of the prosthetic hand on a single user. This demonstrates the potential of this technology to improve the life quality of patients with upper limb amputations.

In the research works,[23-25] authors attempted to implement machine learning based predictive modeling for decoding ERPs and understand the intend of robotic arms. A combination of EEG and EMG is also presented here to demonstrate that the use of such a BCI could improve the performance of a user's control over a robotic arm. The results of the study from Aly *et al*.[24] showed that the hybrid BCI system using both EEG and EMG signals achieved an average classification accuracy of 81.9% for the grasping and releasing task. The extracted features from both EEG and EMG signals were used to train a machine learning model based on a Gaussian mixture model (GMM) to decode the user's intended movement.

Both invasive and noninvasive EEG techniques hold immense significance in clinical settings, especially in the domain of neuroscience and medical practice. Noninvasive EEG is widely used in clinical for diagnosing and monitoring various neurological conditions such as epilepsy, sleep disorders, and brain injuries. It provides valuable insights into brain function and helps clinicians make informed decisions about treatment and management strategies. Invasive EEG, although more invasive and typically reserved for specific clinical scenarios, offers unparalleled precision and detail in recording neural activity.[26] It is crucial for neurosurgical planning, particularly in cases where precise localization of brain regions is required, such as tumor resection or epilepsy surgery. Invasive EEG also plays a significant role in research settings, where it enables scientists to investigate the underlying mechanisms of brain function and develop novel treatments for neurological disorders.

While both invasive and noninvasive methods offer greater spatial resolution and signal quality, they require surgical procedures and carry associated risks. There are relatively fewer works focused on invasive EEG in this domain, indicative of the challenges and limitations associated with invasive procedures. For instance, Beyrouthy *et al*.[27] presented a study on EEG mind-controlled smart prosthetic arms, demonstrating the feasibility of utilizing invasive EEG for prosthetic control. However, the adoption of invasive EEG technologies in prosthetic applications remains limited due to the invasiveness of the procedures and the need for further research to address associated challenges.

Rehabilitation

BCIs have primarily been studied for the purpose of providing assistive technologies to individuals with severe motor disabilities caused by neurodegenerative diseases or strokes. The use of BCIs for enhancing motor and cognitive recovery within neurorehabilitation settings is a newly emerging field of research. While most rehabilitation tools require minimal motor control, BCIs allow patients with severe motor deficits to participate in therapeutic tasks. EEG-based paradigms include sensorimotor rhythms, slow cortical potentials, ERPs, and visually evoked potentials are commonly used in this case.[28]

Several studies have been conducted to assess cognitive functions in paralyzed ALS patients and in patients with physical disabilities due to neurological diseases.[29-33] The evaluation of cognitive abilities in patients with severe motor disabilities is a challenge and a less explored area, but some attempts have been made using ERPs. Three EEG-based modalities (SCP, SMR, and P300) are promising solutions for EEG-BCI system realization. While many studies have demonstrated successful BCI operation, others have shown low performance rates in terms of both CA and ITR.[34] P300-BCI exhibits higher ITRs but is greatly affected by the severity of the disease, while SMR-based BCI systems are adaptive but have the disadvantage of being unreliable for some subjects. Nevertheless, game-oriented solutions seem to be a promising way to enhance user motivation.[35] Despite high-performance rates in some studies, the majority of BCI systems and applications are mainly used in a research environment and have yet to be successfully utilized in patients' homes for continuous and everyday use.[36]

Wheelchair mobility

BCI system aids in wheelchair mobility by allowing individuals with extreme mobility impairment to control the wheelchair's movements using their brain signals. Users can get greater independence and improved mobility through this technology. Independent movement becomes easier for them while navigating their environment with ease. Researchers are conducting extensive experiments and clinical trials in designing such systems. In the context of BCI-controlled hands-free wheelchair navigation.[37,38] Scholars worked on developing a system to detect the user's mental commands and translate them into wheelchair movements, allowing people with severe physical disabilities to operate wheelchairs easily. Permana *et al*.[38] worked on three machine learning models, namely linear discriminant analysis, support vector machine (SVM), and K-nearest neighbors (K-NN), which were trained on the EEG data to classify the mental tasks. The performance of the models was evaluated using accuracy, sensitivity, and specificity measures. The results showed that SVM outperformed the other models with an accuracy of 96.9% in classifying the mental tasks. The results of the study showed that the proposed BCI system using NeuroSky MindWave Mobile 2 can accurately classify mental tasks with high accuracy using the SVM machine learning model.

There are other systems based on motor imagery task stimulation for individuals with severe motor impairment, such as ALS. In one such study Eidel *et al*.[39] worked on a participant who had restricted motor function. Vibrotactile stimuli were applied to four body positions of this patient, and EEG data were recorded from 12 positions (Fz, FC1, FC2, C3, Cz, C4, P3, Pz, P4, O1, Oz, and O2) using a g.GAMMAcap. The EEG data were filtered between 0.1 and 30 Hz, and epochs from 100 to 800 ms around the stimulus onset were created, rejecting epochs as artifacts if they contained excessive values (±75 μV threshold). Similar studies were conducted by Huang *et al*.[40] and Meng *et al*.[41] where a hybrid BCI has been developed to control an integrated wheelchair and robotic arm system.

Edelman *et al*.[42] developed a BCI-enhanced framework that could achieve more than 500% efficiency in pursuing continuous tasks through a real-time control robotic arm. Moreover, Belkacem *et al*.[43] have highlighted the issues related to age-sensitive cognitive functions and how the decline in memory, learning new skills, and paying attention to multiple tasks can affect the quality of life of older people. In addition, the rotation-aligned domain adaptation method with Riemannian mean (RMRA) can effectively handle cross-session and cross-subject issues in BCI, achieving satisfactory results in offline unsupervised and online experiments on different motor imagery EEG datasets.[44]

Virtual reality accessibility

Virtual reality (VR) accessibility represents a significant leap forward in leveraging BCI technology to enhance the virtual experiences of individuals with physical disabilities.[45] BCIs contribute to accessibility in virtual reality, allowing users with physical disabilities to interact within virtual spaces through brain signals.[46] This groundbreaking application empowers individuals by enabling interaction within virtual spaces through the interpretation of brain signals.

In this context, to assist people with visual impairments (PVI), researchers developed VRBubble, an innovative audio-driven virtual reality technique that offers information about surrounding avatars based on their social distances.[47] VRBubble has been evaluated by an audio baseline of 12 PVI through a conversation and navigation context. This advancement in VR accessibility not only promotes inclusiveness but also unlocks fresh opportunities for education and therapeutic applications, enhancing the virtual experience for a wider range of users.[48]

Augmented and alternative communication

Augmented and alternative communication (AAC) encompasses converting neural signals into meaningful communication, providing a lifeline for nonverbal people or facing difficulties in traditional communication methods. Numerous scholars have dedicated their efforts to developing BCI-enabled solutions in this context.[49-52] In one such study,[53] authors attempted to assess how individuals affected by ALS acquired the skill of operating a motor-based BCI switch within the context of a row-column AAC scanning pattern. In addition, the study aimed to explore person-centered factors linked to the performance of BCI-AAC. Such advancement of BCI in AAC offers significant potential to improve individuals' life who are dealing with severe conditions like ALS, cerebral palsy, or paralysis.[54] This technology creates new opportunities for self-expression and social interaction, thereby enriching the overall well-being of individuals facing these challenges.

General medical applications

In addition to transforming health care through advanced neurological assessment and understanding of cognitive processes, BCI technology has also made remarkable advancements in several other medical applications as well. BCI offers innovative solutions that are being used in understanding cognitive processes and providing new equipment for neurological assessment.[55-57] In the realm of general medical applications, significant strides have been developed for patients with neurological disorders, patients who are nonverbal or paralyzed, who have severe attacks from stroke and traumatic brain injuries.[58-61]

Medication optimization

In medication optimization, BCI technology is involved in evaluating the efficacy and potential adverse reactions of medications. By analyzing the brain activity patterns, BCI offers insights into patients' responses to various medications, which might facilitate personalized treatment adjustment and refinement of drug regimens.[62,63] Borgheai *et al*.[61] proposed a predictive model that used a multimodal BCI system with functional near-infrared spectroscopy and EEG. Such predictive models could obtain an R-2 value of a maximum of 0.942 with an average performance gain of 5.18%. Other BCI models in medication optimization include Pharmacovigilance BCI, Pharmacological Neuroimaging BCI, and Pharmacodynamic Response BCI.[64]

Pain management

BCIs contribute to pain management by monitoring neural signals associated with pain perception. This information can be used to develop personalized pain management strategies, including targeted drug delivery or neurostimulation techniques, to alleviate pain and improve patient comfort.[65-67]

Furthermore, BCIs can facilitate the implementation of neurostimulation techniques for pain management. Neurostimulation methods, such as spinal cord stimulation or transcranial magnetic stimulation, modulate neural activity to alleviate pain.[68] BCIs provide real-time feedback on pain levels, allowing for precise adjustments to the parameters of neurostimulation devices to optimize pain relief for individual patients.

While invasive EEG offers unique insights into the neurophysiological mechanisms underlying pain perception and processing, there is limited research in this domain, and recent studies have begun to explore the potential of invasive EEG in understanding and treating chronic pain conditions. In this context, Pu *et al*.[69] conducted a feasibility study on portable EEG monitoring for older adults with dementia and chronic pain, demonstrating the potential for invasive EEG to provide valuable insights into pain experiences in this population. Similarly, the Paired Acute Invasive/Non-invasive Stimulation study by Parker *et al*.[70] investigated the use of invasive EEG in a randomized, sham-controlled crossover trial for chronic neuropathic pain (NP). In addition, the study Lancaster *et al*.[71] demonstrated the feasibility of decoding acute pain using combined EEG and physiological data, highlighting the potential of invasive EEG in improving pain assessment and management strategies. Despite the limited number of studies in this area, the emerging research underscores the importance of further exploring the role of invasive EEG in pain management to advance our understanding and treatment of chronic pain conditions.

Surgical planning

In surgical planning, BCIs aid in preoperative assessments by mapping brain activity to identify critical functional areas and potential risks during surgery.[72] This information guides surgical strategies, minimizes risks, and enhances surgical outcomes by ensuring precise and individualized treatment plans.[73,74] In addition to aiding preoperative assessment, BCI contributes significantly to surgical planning by providing real-time feedback on brain activity patterns. Such feedback allows surgeons to adjust their methods dynamically, ensuring the preservation of critical functional areas and reducing the risk of intraoperative complications during surgery.

Sleep disorder monitoring

Brain activity patterns during sleep can be analyzed. By monitoring neural signals associated with sleep stages and disturbances, BCIs can provide objective data to diagnose sleep disorders, assess treatment effectiveness, and inform personalized sleep management interventions.[75] In one such study, Zhang *et al*.[76] designed a novel sleep disorder treatment system utilizing transcranial microcurrent stimulation. Key technical specifications include adjustable stimulation frequencies of 0.5 Hz, 1.5 Hz, and 100 Hz with two-phase constant current stimulation and continuous adjustment of stimulation currents ranging from 0 to 1 mA. Another established method for diagnosing obstructive sleep apnea is Polysomnography (PSG). Lin *et al*.[77] have devised a PSG system tailored for comprehensive sleep monitoring purposes. It is essential to note that BCI-based sleep monitoring system implementation is still in its early stages, and further research and development are needed to validate its effectiveness and reliability.[78]

Human-computer interaction

BCIs revolutionize HCI by enabling direct communication between the brain and computer systems. This technology allows users to control computers, devices, and interfaces solely through brain signals, offering a novel and intuitive interaction method for individuals with physical disabilities or limitations.[79-81] In this context, Sharma[82] introduced a Multi-Label Sequential Convolutional Neural Network (EM-LSCNN) designed for identifying the facial landmarks of a given face. On implementation and fine-tuning according to the user, this model alters the movement of the mouse indicator across the screen's viewport, eliminating the necessity for a physical mouse. The proposed model exhibited outstanding performance metrics, achieving an accuracy of 98.85%, a precision of 99.20%, an f1-score of 98.65% and a recall of 98.30. In another HCI-related study, Siow *et al*.[83] designed a prototype enabling users to manipulate the cursor by translating real-time synaptic commands. An EEG data collection session was conducted, during which experimental subjects underwent training to master the manipulation of the EMOTIV Insight.

Communication assistance

BCIs provide communication assistance for individuals with speech or communication impairments by translating brain signals into text or speech output. This technology allows nonverbal individuals to communicate effectively, fostering independence, social interaction, and improved quality of life.[84-86] Zhou *et al*.[87] proposed a collaborative robotic arm control system integrating hybrid asynchronous BCI and computer vision technologies. This model merges steady-state visual evoked potentials and blink-related electrooculography (EOG) signals, enabling users to select from 15 commands asynchronously, dictating robot actions within a 3D workspace and reaching targets across a broad movement spectrum. Concurrently, computer vision capabilities are leveraged to identify objects and aid the robotic arm in executing more precise tasks, including automated target grasping.

In another study, Pooya Chanu *et al*.[88] explored electroencephalogram (EEG)-based control of a prosthetic hand. A SVM has been utilized in conjunction with 24-fold cross-validation to classify extracted features. To optimize SVM hyperparameters, a Bayesian optimizer was employed, with a minimum prediction error serving as the objective function. This study showcases the feasibility of utilizing EEG for controlling a prosthetic hand by individuals with motor neuron disabilities.

In the context of communication assistance, invasive BCI technology has prominent potential in the development of speech interfaces, offering a direct link between neural activity and speech production. Research in this area is still emerging; several studies have demonstrated promising results in utilizing invasive BCI for speech control and communication. The study by Leuthardt *et al*.[89] investigated the use of electrocorticography (ECoG) to control a BCI in humans, highlighting the feasibility of using invasive BCI for speech-related tasks. Similarly, Rabbani *et al*.[90] explored the potential for a speech BCI using chronic electrocorticography, further emphasizing the potential of invasive BCI in enabling speech communication for individuals with speech impairments. Invasive BCI research involves more complex procedures, such as the surgical implantation of electrodes, which pose greater risks and ethical considerations compared to non-invasive techniques. Moreover, the high costs associated with invasive BCI research, including equipment, personnel, and medical expenses, are also higher compared to non-invasive BCI experiments. These factors contribute to the scarcity of research in this area of BCI.

Psychology or neurology

BCI applications have promising potential in addressing and managing a wide range of neurological conditions. From detecting Alzheimer's disease, understanding emotional states, and providing deeper insights about therapeutic approaches to diagnosing mental health, BCI has numerous applications.[91,92]

Alzheimer disease treatment

Machine learning algorithms are used to develop various predictive models to decode EEG features, classify information, and provide tailored feedback to the user while assisting neurological disease. Psychological factors such as motivation, attention, and frustration also play an important role in human–machine interaction. da Silva-Sauer *et al*.[93] evaluated the usefulness of BCI systems in promoting cognitive rehabilitation and neuroplasticity in people with dementia. The study involved a total of 10 volunteers with mild to moderate dementia. The tasks included in the study were a motor imagery task, a visual oddball task, and a P300 speller task. In a similar study, Martínez-Cagigal *et al*.[94] created an asynchronous BCI system centered on P300, enabling users to command Twitter and Telegram on an Android device. In this study, the row-col paradigm is employed to stimulate P300 potentials on the user's scalp, which are promptly processed for decoding the user's intentions with motor-disabled individuals.

Depression

BCI provides individuals with real-time feedback on brain activities, which might allow them to engage in neurofeedback training.[95,96] In one study, Widge *et al*.[97] introduced a technology lifecycle framework, indicating that initial trial setbacks result from excessive enthusiasm for an emerging technology. They also suggested that Deep Brain Stimulation might be approaching a phase of significant advancement by merging recent mechanistic discoveries with the maturation of BCI technology. In another study, Liao *et al*.[98] developed a machine learning algorithm that can accurately detect major depression from EEG signals. The authors aimed to use the Kernel Eigen-Filter-Bank Common Spatial Patterns (KEFB-CSP) algorithm to extract discriminative features from EEG signals and train a classifier to distinguish between depressed and nondepressed individuals.

EEG-based interventions could provide a more personalized and effective approach to managing post-stroke depression (PSD) in stroke patients.[99] The effectiveness of electroencephalography (EEG) in managing PSD and improving rehabilitation outcomes is investigated by Yang *et al*.[100] The study also identified significant differences in EEG measures between depressed and nondepressed patients, highlighting the potential of EEG as a diagnostic tool for PSD.

Epilepsy

EEG-based BCIs have advanced significantly in recent years, with promising applications in various fields such as communication, rehabilitation, and entertainment.[101] Sparse representation-based classification methods have shown great potential in EEG signal processing and can significantly improve the accuracy and efficiency of EEG-based tasks, but more research is needed to fully exploit their benefits, especially while treating epilepsy.[102] The potential of direct electrical stimulation (DES) is investigated as an enabling technology for input to the cortex in electrocorticographic (ECoG) BCIs by Caldwell *et al*.[103] Authors suggested that DES can provide a means of generating artificial sensory input or modulating cortical activity to improve BCI performance. Moreover, stereotactic EEG plays a vital role in the evaluation and management of epilepsy, particularly in cases where other diagnostic techniques, such as standard EEG or imaging, have yielded inconclusive results.[104,105]

Emotion classification

BCIs are employed to classify and interpret human emotional states based on brain activity patterns.[106-111] In this context, Teo and Chia[112] worked on EEG data, preprocessed, and segmented into epochs, which were then used to extract spectral features using the Fast Fourier Transform algorithm. The features were fed into a deep learning model consisting of a convolutional neural network and a long short-term memory network. This study suggested that EEG-based excitement detection using deep learning models could have practical applications in areas such as gaming, marketing, and mental health.

In the context of EEG-based emotion classification, the authors proposed a novel approach that combines electroencephalography (EEG) and galvanic skin response (GSR) to capture and classify emotional states. The authors also performed feature selection using a Recursive Feature Elimination algorithm to identify the most relevant features for emotion recognition.[113] The results of the study suggest that the proposed BCI system using EEG and GSR data can achieve high accuracy in recognizing emotions in people with visual disabilities. The Random Forest model achieved the highest accuracy of 84.5% in emotion recognition. Another improved EEG pattern decoding is presented by Zhang *et al*.[114] where one-versus-all encoding is used for propagation-based clustering. Such EEG pattern decoding suggests substantial improvement in brain pattern recognition in BCI.

Seizure

BCI technology has great promise for the improvement of epilepsy management by enabling early seizure prediction and detection, facilitating targeted neuromodulation therapies, and guiding personalized treatment strategies.[115-117] Devices such as neurostimulation (RNS) can be integrated to deliver targeted electrical stimulation to the brain in response to detected seizure activity. Furthermore, BCIs can automatically detect and classify epileptic seizures in real time based on patterns of brain activity. This capability allows for timely intervention, such as triggering responsive devices or alerting healthcare providers, to mitigate the impact of seizures and ensure patient safety.

Stress evaluation

BCI integrated with machine learning models can classify emotional states, including stress. By analyzing different patterns of brain activity, the BCI system can identify when and how an individual experiences stress and to what extent.[116,118] Such research conducted by Lin *et al*.[119] where authors designed a cost-efficient, readily producible, adaptable, durable, and gel-free electroencephalogram (EEG) electrode using a combination of silver nanowires, polyvinyl butyral, and a melamine sponge (AgPMS). This innovative electrode overcomes issues associated with hair interference. Through the silver nanowires' surface metallization, the sponge maintains a high conductivity of 917 S/m without any increase in weight. In another study, Khosrowabadi *et al*.[120] suggested a BCI system that can be applied to categorize the participants' mental stress levels based on the features extracted from their EEG signal data. These features include Gaussian mixtures of EEG spectrogram, Higuchi's fractal dimension of EEG, and Magnitude Square Coherence Estimation among EEG channels. Using the K-NN and SVM algorithms, the classification of these EEG features is carried out.

Cognitive impairment

BCI technology can assist patients with severe cognitive impairment by providing alternative means of communication and interaction. In this way, they can express themselves and engage with their environment using brain signals to control communication devices.[121-124] BCI-based cognitive training tasks, such as memory exercises, attention training, and executive function challenges, provide targeted cognitive stimulation and feedback tailored to individual requirements.

Neuropsychiatric disorder

Neuropsychiatric disorder encompasses a range of mental health conditions, including schizophrenia, bipolar disorder, and major depressive disorder. BCI-based neurofeedback techniques may offer novel therapeutic approaches for managing symptoms of these disorders.[125,126] Numerous researchers have explored different aspects of BCI technology in the field of neuropsychiatric disorders. One notable development is the creation of an estimation and classification system that considers age and gender factors while utilizing structural magnetic resonance imaging (sMRI) brain images.[127] This system aims to improve the accuracy of diagnosing and classifying neuropsychiatric disorders by incorporating demographic variables and leveraging advanced neuroimaging techniques. By integrating BCI with sMRI data, researchers seek to enhance our understanding of these disorders' neural mechanisms and develop more effective diagnostic and treatment strategies tailored to individual patients.

Anxiety assessment

Anxiety assessment refers to evaluating and managing anxiety disorders, such as social anxiety disorder, generalized anxiety disorder, and posttraumatic stress disorder (PTSD). By analyzing patterns of brain activity associated with stress and arousal, BCI can aid in providing the biomarkers of anxiety.[128-131] Such BCI-enabled designs can enhance the accuracy of anxiety assessment. Other applications include informing treatment decisions and facilitating the development of novel interventions, such as BCI-based biofeedback training for anxiety regulation.

Attention-deficit/hyperactivity disorder

Attention-deficit/hyperactivity disorder (ADHD) is a neurodevelopmental disorder marked by challenges in sustaining attention, managing impulses, and regulating activity levels.[132,133] BCIs have the capability to monitor attentional processes in real time by observing patterns of brain activity associated with attentional engagement and disengagement. BCIs can adjust task parameters or provide motivational cues based on real-time assessments of attentional state, facilitating task completion and goal attainment.[134,135] In one study, Lai *et al*.[136] combined BCI technology with Tangible User Interface (TUI) techniques and introduced the prototype of a TUI jigsaw puzzle, named E-Jigsaw, aimed at assisting children with attention deficit disorder and Attention Deficit Hyperactivity Disorder. E-Jigsaw incorporates an interactive design that aligns with neural feedback mechanisms. Its TUI functionality is designed to enhance hand-eye coordination, precise manipulation skills, sensory integration ability, and attention levels through engaging user interactions. Furthermore, for real-time attention monitoring, Prabhu *et al*.[137] introduced a novel smart wearable headband prototype that combines EOG and EEG sensors. This advanced device facilitates the continuous tracking of brain activity and eye movements in real-time during various activities. This capability enables the detection of subtle shifts in alertness, attention, and perception.

Pediatric applications

In pediatric health care, there are numerous innovative solutions for diagnosis, treatment, and rehabilitation. Cognitive function can be measured through such technology in pediatric patients, assisting clinicians in assessing attention, memory, and executive function skills. This application can be further segmented into pediatric neurorehabilitation and neurodevelopmental monitoring.

Pediatric neurorehabilitation

Pediatric neurology research is based on investigating brain-behavior relationships, neural mechanisms of development, and biomarkers of neurological disorders in children. By studying brain activity patterns, BCIs enhance our understanding of pediatric neurological conditions, facilitating early diagnosis, intervention, and personalized treatment approaches.[138,139] Hasan *et al*.[126] conducted a study utilizing a potential diagnostic biomarker for NP. The anticipated insights from this research hold significant clinical relevance in the development of neurofeedback-based neurorehabilitation and connectivity-based BCIs for patients with SCI.

Neurodevelopmental monitoring

Neurodevelopmental monitoring entails methodically observing and evaluating a child's neurological and cognitive development over time. This process allows healthcare professionals to track developmental milestones, identify potential delays or disorders, and provide early intervention and support when necessary.[140,141] By monitoring neurological development from infancy through childhood, clinicians can detect and address neurodevelopmental concerns early, promoting optimal outcomes for children's cognitive, social, and emotional well-being.[142,143]

Personalized medicine

Personalized medicine through this technology involves tailoring medical treatments and interventions to individual patients based on their unique neural activity patterns, cognitive abilities, and clinical characteristics. By leveraging BCI technology, healthcare providers can obtain real-time insights into patients' brain function and neurological status, allowing for more precise diagnoses, treatment plans, and therapeutic interventions.[144] This personalized approach enhances the effectiveness of medical care by accounting for variations in patients' physiological responses, preferences, and treatment outcomes, ultimately enhancing patient results and overall well-being.[145]

Neurofeedback therapy

Neurofeedback therapy has been used to address a variety of neurological and psychological conditions, including attention deficit ADHD, anxiety, insomnia, traumatic brain injury, depression, epilepsy, and PTSD.[146,147] It is also used for peak performance training in athletes, musicians, and other professionals seeking to enhance cognitive function and concentration.[148,149]

Tailoring therapy dosages could potentially optimize improvements in motor functions. Bigoni *et al*.[150] developed a therapeutic approach involving two consecutive interventions, continuing until the patient demonstrates no additional motor enhancement, with a minimum of 11 sessions each. The key outcome in this study is defined as a 4-point enhancement in the Fugl-Meyer assessment of the upper extremity, which was achieved in the initial patient, showing an elevation from 6 to 11 points between T0 and T2. This progress was accompanied by alterations in the structure and function of the motor network.

Individual treatment planning

Individual treatment planning involves customizing medical interventions and therapies to align with the specific needs, characteristics, and preferences of each patient. This approach recognizes that individuals may respond differently to treatments due to factors such as genetics, lifestyle, coexisting conditions, and personal preferences. By customizing treatment plans for each patient, healthcare providers can maximize the effectiveness of interventions, minimize adverse effects, and improve patient outcomes.[151-153] ciBCI technology can have a significant impact on individual treatment planning by providing insights into patients' neural activity, cognitive function, and real-time responses to interventions.[154]

Discussion

BCI technology integration shows considerable potential across a wide array of fields. In the realm of medical applications, BCI technology plays a crucial role in enhancing accessibility and improving outcomes for individuals, especially those with disabilities. By harnessing BCI-controlled assistive devices such as prosthetics, wheelchairs, and communication aids, patients are empowered to regain autonomy and enhance their quality of life, conquering the obstacles to mobility and communication.

Furthermore, BCI-driven neurorehabilitation programs offer tailored therapies for patients recovering from neurological traumas or conditions. These programs facilitate motor recovery, cognitive rehabilitation, and functional independence through personalized interventions. This review work significantly contributes to advancing the understanding and application of BCI technology in medical contexts. By synthesizing and consolidating a diverse range of related research, our review paper provides a comprehensive overview of the field's current state.

While such technology has promising positive impacts in medical domains, there are still several limitations to consider. The reliability of BCI systems in real-world settings requires further validation. Variability in EEG signals due to factors such as electrode placement and signal artifacts might impact the accuracy of the results, which should be considered carefully. The papers discussed in section communication and assistive device section[49-52] have limitations in discussing and identifying long-term assessment for sustained efficacy and usability of such BCI devices. In studies focusing on Alzheimer's disease and depression,[95,96] ethical considerations play a significant role, particularly while obtaining informed consent from participants. Given the sensitive nature of such neurological and psychiatric conditions, ensuring that participants fully understand the nature of the research, its potential risks and benefits, and their rights as research subjects is paramount. In addition, researchers must adhere to ethical guidelines and regulations governing the conduct of research involving human participants, including protocols for data confidentiality, privacy protection, and respectful treatment of participants. By prioritizing ethical considerations, researchers can uphold the integrity and validity of their findings while safeguarding the welfare and autonomy of research participants.

Moreover, another potential limitation in this BCI medical application indicated that technology such as neurodevelopment monitoring[142,143] and neurofeedback therapy[138,139] could pose barriers to widespread adoption due to the expenses. Addressing the financial barrier to adopting BCI technology in the medical field requires collaborative efforts. It includes necessary input from researchers, healthcare providers, policymakers, and industry stakeholders to develop cost-effective solutions, advocate for insurance coverage of BCI services, and increase funding for BCI research and development. By overcoming these financial challenges, the benefits of BCI technology can be more equitably accessible to individuals in need of innovative medical interventions and treatments.

Moreover, although extensive research has been conducted on both noninvasive and invasive BCI systems, noninvasive techniques, particularly EEG-based approaches, are being more widely studied due to their lower risk and ease of implementation. However, despite notable advancements, various gaps remain in the development of effective, accessible, and adaptable BCI solutions. Key areas, including the balance between invasiveness and control, scalability of subject-independent BCIs, and personalization for specific user needs, still require further exploration to improve real-world applicability and user experience. Considering the technological limitations, the majority of research focuses on noninvasive BCIs (e.g., Murphy *et al*.,[7] Joadder *et al*.,[9] Toma[10]), which utilize EEG signals for BCIs. While this method is less risky than invasive methods, it may lack the precision and control that invasive approaches offer.

Invasive BCIs (e.g., Laiwalla *et al*.,[20] Flesher *et al*.[25]) have shown potential in providing fine control and even sensory feedback for prosthetics. However, there are fewer studies in this area due to ethical concerns and technical challenges. Gap: More research could be directed toward balancing the precision of invasive BCIs with the safety and accessibility of noninvasive ones. In addition, research works by Ang *et al*.[30] and Ang and Guan[31] focus on real-time feedback and rehabilitation using EEG signals to improve motor recovery, but there is limited focus on personalized BCI adaptations for rehabilitation. Gap: Research could delve into creating adaptable BCIs for specific user needs in rehabilitation and prosthetics, improving personalization and feedback mechanisms. Tables 1-3 provides thorough comparative analysis. Table 1

Table 1: Comparison between invasive and noninvasive methods

Reference paper	Year	Methods	Focus area
Murphy *et al*.[7]	2017	Noninvasive	Based on advances EEG-based interfaces
Joadder *et al*.[9]	2019	Noninvasive	Focus is on subject-independent BCI system
Toma[10]	2023	Noninvasive	Procedures undertaken in a passive BCI
Kwon *et al*.[14]	2020	Noninvasive	Use of deep learning for subject-independent BCI
Manyakov *et al*.[15]	2011	Noninvasive	P300 BCI classification
Cantillo-Negrete *et al*.[16]	2023	Noninvasive	BCI-controlled functional electrical stimulation
Guger *et al*.[17]	1999	Noninvasive	EEG-based prosthetic control
Katyal *et al*.[19]	2014	Noninvasive	Collaborative BCI for prosthetic control
Laiwalla *et al*.[20]	2019	Invasive	Discusses implantable microstimulators
Chapin *et al*.[21]	1999	Invasive	Real-time control using recorded neurons
Oppus *et al*.[22]	2016	Noninvasive	BCI for 3D printed prosthetic hand
Mishchenko *et al*.[23]	2018	Noninvasive	EEG-based interface
Aly *et al*.[24]	2018	Noninvasive	Hybrid BCI for upper limb prostheses
Flesher *et al*.[25]	2021	Invasive	BCI that evokes tactile sensations
Fifer *et al*.[26]	2013	Invasive	Development of advance prosthetic device using iEEG for high-resolution neural signals
Beyrouthy *et al*.[27]	2016	Noninvasive	Controlling smart Prosthetic arm through brain activity using EEG
Ang *et al*.[30]	2015	Noninvasive	Controlling robotic rehabilitation device through brain activity measured via EEG
Ang and Guan[31]	2015	Noninvasive	To enhance motor recovery by providing real-time feedback and to encourage therapeutic environment
Savić *et al*.[33]	2023	Noninvasive	Electrotactile BCI utilizing somatosensory to create feedback loop that improve sensory function and motor control
Séguin *et al*.[36]	2023	Noninvasive	P300-based BCI focuses on enabling communication and control devices for individuals with limited mobility

BCI – Brain-computer interface; EEG – Electroencephalogram; 3D – Three-dimensional

Table 2: Comparison between machine learning or deep learning models

References paper	Year	ML/DL techniques	Focus area
Manyakov *et al*.[15]	2011	BLDA, LDA, SWLDA, FE, SVM, neural network and nSVM	They used classification algorithm for P300-based BCI for communication aid
Meng *et al*.[36]	2016	Two sequential low-dimensional control strategies (SVM)	They used BCI approach based on machine learning to control robotic arm with precision
Deng *et al*.[40]	2023	Quadcopter cluster control based on SSVEP (canonical correlation analysis)	VR-based BCI, interactive, designed for controlling unmanned aerial vehicle swarm
Karas *et al*.[44]	2023	Neural network (supervised clustering algorithm)	Develop a unique double-thresholding based pattern recognition approach to detect eye artifacts in EEG signals
Borgheai *et al*.[56]	2024	MLR	Prediction of BCI performance by applying machine learning models
Li *et al*.[61]	2024	BCI-based motor image	BCI training program incorporating both visual and motor feedback for stroke rehabilitation
Widge *et al*.[92]	2018	Deep reinforcement learning	Closed loop DBS that uses real-time feedback from brain activity for treatment-resistant depression
Garima *et al*.[104]	2023	Flexible analytic wavelet transform for dimension and random forest for emotion classification	Dimensionality reduction and visualization of high-dimensional EEG data for emotion classification
Teo and Chia[107]	2018	DNN using 10-fold cross-validation	Leveraging deep learning approach for EEG-based excitement detection in VR
Pinilla *et al*.[108]	2023	LME models and RFECV	Real-time affect detection in VR using 3D model Aims to approve the accuracy of emotion recognition
Zhang *et al*.[109]	2021	Clustering-based multitask feature learning algorithm (propagation-based clustering)	The study area focuses on multitasking learning to enhance EEG decoding for various cognitive and emotional plan
Kwon *et al*.[9]	2019	CNNs	Use of deep learning for subject-independent BCI
Silversmith *et al*.[112]	2021	EEG, fMRI, signal processing, and machine learning algorithm	Developing the system that can adjust to the changes in neural signals allowing for reliable and user-friendly BCI control
Khosrowabadi *et al*.[115]	2011	K-NN and SVM	Uses various methods (such as Higuchi's fractal dimension) for analyzing EEG signals to detect and classify level of mental stress
Akrami *et al*.[120]	2024	KSVM, RF, and neural network	Employ machine learning to analyze the imaging data and predict outcomes that help in early identification of traumatic epilepsy
Arsalan and Majid[126]	2022	RF classifier	Develop a headband to monitor EEG signals that focuses on differentiating various levels of anxiety detection
Demarest *et al*.[136]	2024	Theta-controlled BCI, pain neuromatrix	BCI utilizes theta brainwave pattern to explore chronic pain treatment management

BCI – Brain-computer interface; KSVM – Kernel Support Vector Machine; K-NN – K-nearest neighbor; SVM – Support vector machine; EEG – Electroencephalogram; CNNs – Convolutional neural networks; LME – Linear mixed-effects; RFECV – Recursive feature elimination with cross-validation; MLR – Multivariate linear regression; VR – Virtual reality; fMRI – Functional magnetic resonance imaging; SSVEP – Steady-state visual evoked potentials; 3D – Three-dimensional; DBS – Deep Brain Stimulation; DNN – Deep neural network; LDA – Linear discriminant analysis; RF – Random forest; BLDA – Bilevel discriminative learning algorithm; SWLDA – Stepwise linear discriminant analysis; FE – Feature engineering; ML – Machine Learning/DL – Deep Learning; SVM – Support vector machine

presents a comparison of invasive versus noninvasive BCI, highlighting key distinctions. Table 2 focuses on studies that incorporate machine learning or deep learning models, allowing for a detailed examination of algorithmic approaches. Finally, Table 3 summarizes the practical applications of the reviewed studies, offering an overview of how BCI technologies have been implemented across various contexts.

Through this systematic segmentation, discussion, and referencing of numerous relevant studies, our review explicates key findings, identifies emerging trends, and highlights gaps in knowledge. By shedding light on the multifaceted applications of BCI technology in health care, this work serves as a valuable resource for researchers, clinicians, and stakeholders seeking to harness the full potential of BCI technology in improving patient care and outcomes. We have another ongoing work which focuses on the multimodal emotion recognition in BCI settings that exemplifies this direction, merging EEG signals with synchronized facial or physiological data to improve emotion detection accuracy. Such models hold promise for personalized interventions, where emotion-aware systems could adapt in real time to a patient's emotional state, thereby enhancing clinical engagement and treatment efficacy.

Table 3: Comparison based on general applications

References paper	Year	Focus area	Sub-areas
Lyu *et al*.[57]	2023	BCI in healthcare	Human factor engineering and user satisfaction in BCI systems
Popa *et al*.[58]	2023	BCI in healthcare	Noninvasive system in TBI rehabilitation
Colamarino *et al*.[59]	2023	BCI in healthcare	BCI to enhance recovery of arm function after Spinal cord injury
Sengupta and Lakshminarayanan[60]	2024	Cognitive and neuroscience	Performance analysis of BCI in tactile imagery (cortical activation during tactile vs. motor imagery)
Borgheai *et al*.[61]	2024	BCI in healthcare	Multimodal prescreening for BCI performance prediction (predictive modeling)
Ghumman *et al*.[62]	2021	BCI in healthcare (medication optimization)	Enhanced EEG-based BCI performance, parameter optimization
Ma *et al*.[63]	2022	Cognitive and emotional state recognition	Personalized medical applications
Araújo *et al*.[65]	2024	Pain management and neurological disorder	Remediating phonological deficits in dyslexia treatment with BCI
Li *et al*.[66]	2024	Pain management (general health application)	BCI training for stroke rehabilitation
Yang and Yanagisawa[67]	2024	Pain management/clinical research	Phantom limb pain awareness and treatment
Calzone and Grossman[68]	2024	General health application	Blunt cardiac injury management
Pu *et al*.[69]	2021	General health application	Monitoring dementia and chronic pain with portable EEG
Parker *et al*.[70]	2021	Pain management and neurological disorders	Stimulation study for chronic neuropathic pain treatment
Downey *et al*.[81]	2018	General health application	Decoding acute pain with EEG BCI usability and stability assessment
Metzger *et al*.[86]	2024	Innovative approach in BCI	Communication (silent-speech BCI) for severe anarthria patients
Zhou *et al*.[87]	2023	Innovative approach in BCI	Shared robotic arm control using BCI and computer vision (robotic assistance for rehabilitation)

BCI – Brain-computer interface; EEG – Electroencephalogram; TBI – Traumatic brain injury

Conclusions

BCI technology has introduced new possibilities in medical research, diagnosis, and treatment by enabling direct communication between the brain and external devices. From predictive analytics to neurofeedback therapy, BCI is reshaping the landscape of health care, offering unprecedented insights and capabilities. By enabling control over assistive devices such as prosthetics, wheelchairs, and communication aids, BCI technology empowers patients to regain autonomy and quality of life, addressing barriers to mobility and communication. This survey work represents a pivotal milestone in the field of BCI technology, particularly in its applications within the medical domain by synthesizing a wide array of research findings. This systematic categorizing of the diverse applications of BCI technology will serve as an indispensable guide for shaping future research directions. And researchers in this field might gain a depth understanding of the current landscape of BCI technology in medical applications. By highlighting key findings, identifying trends, and pinpointing areas for further investigation, this paper offers invaluable insights that can inform the development of innovative BCI-based solutions for healthcare challenges.

Author contributions

Meenalosini Vimal Cruz - Conceptualization, Methodology, Resource Collection, Writing, Validation, Review, Supervision, project administration; Suhaima Jamal - Investigation, Paper collection, writing and draft preparation, formatting, Analysis, editing, Visualization; Sibi Chakkaravarthy - Conceptualization, Review, Proof reading.

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