IJHSR ijhighschoolresearch.org
REVIEW ARTICLE

Brain-Computer Interfaces: A Comprehensive Review of Technologies, Applications, and Challenges

Honglin Zheng

Furen International School, 8 Claymore Hill, Singapore, 229572, Singapore; ethanhl529@gmail.com
Mentor: Marcin Kedziera

ABSTRACT: Brain-computer interfaces (BCIs) are advanced systems that bypass traditional neuromuscular pathways to establish a direct communication path between the brain and external devices. This literature review takes an in-depth look at BCIs, tracing their evolution from early electroencephalogram (EEG) discoveries to contemporary applications. The review divides BCI technologies into invasive and non-invasive approaches, analysing their respective advantages and limitations. Invasive BCIs provide high-resolution neural data but carry significant risks, while non-invasive BCIs, while safer, generally have lower accuracy rates. The review highlights the current state of BCI applications in medical and non-medical fields, such as restoring motor function in disabled patients and enhancing the gaming experience. In addition, this article also explores the challenges currently faced by BCIs in terms of signal noise, electrode design, ethical considerations, and regulatory frameworks. The future direction of BCIs depends on advances in hardware (including flexible electrodes and wireless systems) and software (especially in improving decoding accuracy and AI integration). Despite significant progress, continuous improvements are still needed before BCIs can be widely implemented.

KEYWORDS: Biomedical Engineering, Biomedical Devices, Brain-Computer Interface, Cognitive Enhancement.

Introduction

Definition of Brain-Computer Interfaces (BCIs):

A brain-computer interface (BCI) is a system that establishes a direct communication pathway between an individual's brain and an external device. It is a technology that enables fast and accurate two-way information exchange. These interfaces are designed to intercept, analyse, and interpret neural signals, allowing the brain to eventually control software or hardware directly – without relying on traditional neuromuscular pathways.[1,2] BCIs can be broadly categorised into invasive and non-invasive interfaces. These devices can be used for a variety of purposes, including helping disabled people restore functions, such as movement and speech, as well as facilitating interaction with computing devices for gaming and entertainment.[3] BCIs are also one of the few technologies that have the potential to directly help people with amyotrophic lateral sclerosis (ALS)[4], stroke[5], or spinal cord injury[6] regain functions such as walking and communicating. This literature review will cover the neuroscience, state-of-the-art applications, and hardware and software challenges of BCIs. It is also the first literature review on BCIs to review a primary source interview with a patient who has been implanted with Neuralink® Corp's invasive BCI. This article focuses on reviewing the prospects for the development and application of BCIs and the current issues that need to be addressed.

Brief History and Evolution:

In 1924, Hans Berger[7] recorded the first electroencephalogram (EEG). This showed that the brain's electrical activity could be artificially captured. Later, in the 1960s, Grey Walter[8] conducted early experiments using EEG to study brain wave activity during various states of consciousness. His work showed that EEG signals could be linked to different psychological states and responses. Then, in 1969, Eberhard Fetz[9] showed that monkeys were able to learn to consciously control the firing rate of individual neurons in the brain when motivated by food rewards. His experiments showed that neuronal activity could be used to control external devices.

It was not until 1973 that the term "brain-computer interface" was defined by Jacques Vidal.[10] He proposed the possibility of establishing a direct communication path between the human brain and the computer instead of traditional muscle input. Through electroencephalogram to capture brain signals, these signals can be used to control external devices. In the 1990s, Philip Kennedy[11] implanted the world's first brain-computer interface in a stroke patient, and brain-computer interface research has developed rapidly since the beginning of the 21st century.

Principle of Neural Signaling:

Neurons play a vital role in the transmission of nerve signals and are the most basic structural and functional units of the nervous system. Although past studies have found hundreds of unique morphologies of nerve cells, their main components are the cell body, which has two additional unique structures: the axon and the dendrite. The cell body contains the nucleus and organelles and is responsible for the metabolic work of the neuron. The long, thin, branch-like filaments surrounding the neuron are divided into dendrites and axons.

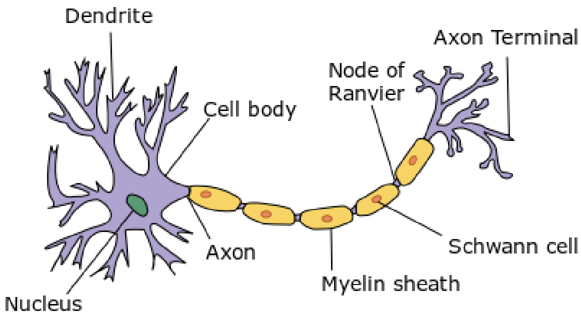

Figure 1: The cell body contains the nucleus and most of the cell organelles. Dendrites are multiple branches extending from the cell body. The axon extends a long fibre from the cell body. Myelin is the fatty layer that wraps around the axon of a neuron, insulating it and allowing the action potential to propagate faster and more efficiently. Schwann cells are a type of glial cell in the peripheral nervous system that produces myelin. Nodes of Ranvier refer to the small gaps between adjacent Schwann cells on a myelinated axon.[12]

Dendrites are short, branched structures that extend directly from the cell body, as seen in Figure 1. They mainly receive signals from other neurons. Axons are longer and have fewer branches. They are long, thin protrusions of uniform thickness that usually originate from the axon hillock and transmit signals to other neurons or muscles.[13] A synapse is a specialized junction at which a neuron communicates with a target cell. In the nervous system, signals transfer primarily through synapses. Neuronal signal transmission is divided into multiple stages. Neurons first receive chemical signals from the axon terminals of other neurons at synapses on dendrites. When a neuron receives a strong enough stimulus, the sodium ion channels on the cell membrane open, and sodium ions quickly enter the cell, causing the membrane potential to rise. When the membrane potential reaches the threshold, an action potential is triggered, generating a corresponding electrical signal. The action potential is transmitted along the axon to the distal end. When the action potential reaches the axon terminal (presynaptic membrane), it triggers the opening of calcium ion channels. As calcium ions flow into the axon terminal, they release neurotransmitters stored in vesicles into the synaptic cleft. Finally, the neurotransmitter diffuses to the postsynaptic membrane and binds to specific receptors, which causes the opening of sodium ion channels, triggering the depolarisation of the postsynaptic neuron, thereby transmitting the signal. If the threshold is reached again, the neuron will generate a new action potential, thus forming a cycle. In addition, once neurotransmitters complete signal transmission, they are degraded by enzymes in the synaptic cleft or reabsorbed by the presynaptic membrane to terminate signal transmission and prepare for the next signal. The neurotransmitters secreted by neurons can also be divided into excitatory transmitters or inhibitory transmitters to further regulate the response of neurons, thereby completing more sophisticated neural network activities.[14]

Discussion

Invasive BCIs:

Invasive brain-computer interfaces involve implanting electrodes either on the surface of the brain or deeper within the brain tissue. As a result, these interfaces are often able to provide higher resolution and more precise control relative to non-invasive methods. Invasive BCIs bypass the skull and scalp, so they are less susceptible to distortion and attenuation of electrical signals. These electrodes detect neural activity, amplify the signals, decode them through algorithms, and ultimately translate them into commands that control external devices or computer systems.[15] There are currently two main types of invasive electrodes: electrocorticographic electrodes and intracortical electrodes.

Electrocorticogram (ECoG)[15,16] electrodes are a less invasive method than intracortical electrodes and are usually placed directly on the surface of the cerebral cortex during surgery. Compared with EEG electrodes placed on the scalp, ECoG electrodes are closer to the neuronal structures of the superficial cortex. Therefore, the signals they record have higher amplitudes and wider frequency bandwidths. Although non-invasive electrodes such as EEG can also record the synchronous activity of neurons and synapses in extended areas of the cortex, ECoG electrodes are more sensitive to smaller sources of synchronous neuronal activity and have higher reliability. At the same time, scientists have found that ECoG appears to be able to detect higher-frequency amplitudes more effectively, and the information carried in high-frequency signals is usually more critical, including cognitive, motor, and language tasks. This information is difficult to obtain with non-invasive electrodes such as EEG.[16] This makes it of great significance in clinical applications, such as brain function mapping before surgery for epilepsy patients and brain-computer interface research requiring precise neural data. The technology strikes a good balance between signal quality and invasiveness and is less likely to cause unpredictable damage than deeper implants.

Intracortical electrodes can penetrate brain tissue and receive signals from single neurons, recording or stimulating neural activity with excellent precision. They provide better recording quality than less invasive techniques such as ECoG, as they can record different types of signals (single and multi-unit activity and local field potentials) and provide the best spatial and temporal resolution.[15] However, a significant disadvantage of using intracortical probes is that they have a limited lifespan due to their highly invasive nature, and the quality of the recorded signals tends to deteriorate over time. In studies on rats, despite the use of probes of various materials, shapes, and sizes, the effects of foreign body reactions (FBRs) have not yet been fully overcome.[17,18]

Non-invasive BCIs:

The most obvious difference between the non-invasive brain-computer interface and the invasive brain-computer interface is that the former does not require surgical implantation of electrodes. This makes it much safer than invasive BCIs, avoiding the various risks caused by damaging the skin and implanting electrodes in the body. So far, there are many ways to achieve non-invasive brain-computer interfaces, such as electroencephalogram (EEG),[19-21] magnetoencephalogram (MEG),[22] functional near-infrared spectroscopy (fNIRS),[23] and transcranial magnetic stimulation (TMS).[24] They all have different characteristics and are suitable for different scenarios.

EEG is currently the most popular method for signal acquisition for brain-computer interfaces. EEGs can obtain information about brain activity by measuring voltage fluctuations caused by the flow of ionic currents within brain neurons.[19] They can measure changes in brain activity within a few milliseconds. Since their introduction, more than 90 years ago, EEG systems have been widely used in many fields. As a result, the signal acquisition methods and techniques of this technology have been standardised. Today, most EEG electrodes are arranged in the internationally standardised 10-20 system.[19] Placing multiple electrodes on the scalp can obtain different views of the brain's electrical activity.

Compared with invasive BCI, EEG-based methods have the advantages of no surgical risk, stable signals, and relatively low cost. However, due to the blurring effect of the skull and scalp, the spatial resolution of EEG is relatively low. This limits the accuracy of neural signals. At the same time, EEG signals may be contaminated by non-brain activities like eye movements and muscle artifacts. In addition, individual differences in skull thickness, skin conductivity, and other factors can affect signal quality.[20] This requires custom adjustments to EEGs to accommodate differences in individual physical characteristics. Over the past few decades, EEG-based BCIs have been developed to restore motor skills to stroke patients or to provide the possibility of communication for patients with ALS or locked-in syndrome.[21]

In addition to EEG, other non-invasive detection methods are less common in applying brain-computer interfaces. Magnetoencephalography is an advanced neuroimaging technology that maps brain activity by recording magnetic fields in the brain.[22] Neurons in the brain produce currents and magnetic fields when they communicate, and these magnetic fields are measured using highly sensitive superconducting quantum interference devices. This method has a precise temporal and spatial resolution, but it is very demanding on the use environment and expensive to fake, requiring the construction of specially shielded rooms. This prevents MEG from being widely used. Functional near-infrared spectroscopy measures brain activity by detecting changes in blood flow and oxygenation in the cerebral cortex.[23] When activity in a specific brain area increases, it leads to higher oxygen consumption. Haemoglobin in the blood, which contains different concentrations of oxygen, absorbs light of various wavelengths so that when it is illuminated by infrared, the brain's activity can be detected by changes in the spectrum. However, this also results in lower spatial resolution than that of technologies such as MEG, and it cannot effectively measure deeper brain structures.

Applications of BCIs:

The pace of progress in brain-computer interface research is rapid: this includes advances in hardware and software,[25,26] progressing medical applications and clinical trials of BCIs,[28-31] and other fields like neuro-gaming.[31]

Medical Applications:

The ageing population in the world is currently increasing, and many ageing-related diseases and mobility issues are plaguing elderly people.[27] The idea of using external mechanical structures to enhance the physical abilities of the human body was proposed decades ago.[28] Soon, mechanical exoskeletons, driven by brain-computer interfaces, can enhance the physical abilities of the human body through mechanical structures attached to the body to assist walking. These exoskeletons can directly recognise neural signals from the brain without relying on neural signal control at the amputation site. This device structure could improve the lives of elderly people with underlying diseases and limited mobility. Currently, the preliminary exoskeleton structure has been formed, and basic functions have been achieved.[29]

Another exciting medical application of BCIs is communication restoration. Language is an important way for humans to express and convey information. However, at present, many people have lost their ability to speak due to disease and suffer from aphasia. Famously, Stephen Hawking suffered from amyotrophic lateral sclerosis and almost lost all his ability to express himself in the late stage of the disease. The brain-computer interface provides the possibility of more accurate expression, converting brain signals into words or audio output through the voice brain-computer interface. However, one of the biggest limitations of this technology is the limitation of flexible recognition. BCI needs additional information to assist recognition; the user's intention is transmitted indirectly. In the experiment from the team of Seo-Hyun Lee, most experimenters need vocalization or other actions to assist BCI in recognizing the information the brain wants to convey.[30]

In May 2024, an invention by researchers at the California Institute of Technology[31] provided the possibility to recognise internal speech - speech synthesis using brain signals originating in the imagination. This is a significant breakthrough in this technology. The technology detects and decodes neural signals by implanting probes into the limbic gyrus (SMG) area of the brain of quadriplegic patients. Judging from the results of the two participants, the recognition of internal speech reached an average accuracy of 79 percent and 23 percent. The technology is still in the development stage, but once the technology matures, it will greatly improve the lives of patients who have lost the ability to speak.

Non-medical Applications:

In non-medical areas, brain-computer interfaces are also showing great potential for development. There have been many successful implementation cases in gaming. An ideal brain-computer interface would allow the brain to directly control game elements. Players could use their thoughts to control virtual characters, navigate environments, and execute commands, thereby gaining a more immersive gaming experience. For example, an experimenter used the Muse 2® EEG headband to obtain EEG data and then used the OpenViBE® platform to process the signals and classify them into three different mental states: left and right motion images and blinking. Based on this, the experimenter designed a simple 3D game

 DOI: 10.36838/v7i4.36

that can control the character, move and jump left and right, and collect coins on the way to get higher scores. Among the 33 subjects who participated in the experiment, the classification algorithm of the multi-layer perceptron (MLP) obtained an accuracy rate of 96.94 percent.[32] This demonstrates the feasibility of brain-computer interfaces for simple games.

In addition, several research reports have been published on monitoring attention through brain-computer interfaces. For example, in blended learning at universities, using non-invasive electroencephalogram (EEG) instruments to collect attention data can effectively record changes in students' attention during classroom learning, thereby informing teaching methods and achieving higher learning efficiency.[33] Furthermore, brain-computer interface data can even be used for deception identification. In many criminal cases, it is difficult for investigators to confirm whether suspects are lying. Recent studies have shown that EEG data may be one of the options for identifying deception in the future.[34]

Challenges:

Among the challenges currently faced by brain-computer interfaces, electrodes are undoubtedly important. Today, most electrode tests are still in the laboratory and have not been tested *in vivo*. Flexible electrodes are a good choice for brain-computer interfaces. In theory, flexible electrodes can improve accuracy, reliability, and sensitivity and bring a better comfort experience. The mechanical properties of flexible electrodes can effectively increase the contact area and reduce motion artifacts. Today, there are two design ideas for flexible materials. One is to add conductive substances to the flexible matrix and then make it by physical mixing. The other is to deposit or electroplate conductive materials on the flexible substrate.[35] However, due to the complexity of the human body, whether flexible electrodes have wide applicability still needs further testing.

For the electrode structure design of non-invasive brain-computer interfaces, the long-term durability of wet electrodes and semi-wet electrodes has been criticised.[35] With long-term use, the conductive paste of the wet electrode and the saline stored in the semi-dry electrode will gradually evaporate, resulting in a significant increase in skin contact impedance and signal distortion, thereby affecting sensitivity. Although dry electrodes avoid the above problems, their coating is easy to peel off, resulting in increased electrode impedance. In addition, the design and preparation of dry electrodes is more complicated.

For invasive brain-computer interfaces, the hardness of common electrode materials is often far greater than that of the brain, making it easier to damage the brain. New, softer materials are required to solve these problems. In addition, the structural design of invasive electrodes is also a major challenge. It requires a structure that can avoid severe compression and damage to nerves to the greatest extent possible and achieve better signal recording, higher signal-to-noise ratio, and more stable impedance.[35,36]

In summary, the main challenges faced by electrode design are as follows:

- The fine-tuning of chemical and physical properties of materials, with low impedance and good antioxidant and corrosion resistance (such as conventional human sweat erosion), while maintaining sufficient flexibility.
- The structural design of the electrode, with a good structure to obtain clearer signals and lower interference.
- Biocompatibility, whether the electrode will cause damage to human health.
- The difficulty and comfort of practical application, whether the final use of the electrode requires cumbersome operation, and whether the wearer can experience the brain-computer interface comfortably.

These challenges still require scientists to conduct further research and exploration to solve.

Signal noise and accurate decoding are the other two critical challenges in the development and implementation of brain-computer interfaces (BCIs). This is because the neural signals of the human brain are usually weak and may be contaminated by various noise sources, resulting in low signal-to-noise ratio, inaccurate data interpretation, and leading to unreliable BCI control. Noise, artifacts, or interference are redundant and unwanted fluctuations in the primary signal acquired by the brain-computer interface. This signal interference mainly comes from various electromagnetic sources such as AC power supplies or electronic devices such as computers and routers. Physiological noise and artifacts come from muscle activity (electromyography, EMG), eye movement (electrooculogram, EOG), and heartbeat (electrocardiogram, ECG). These artifacts and noise can mask or distort the real neural signals, complicating data analysis and interpretation. Therefore, effective noise and artifact removal techniques are essential to improve BCI performance.[37]

Ethics and Regulations:

In the past two decades, as brain-computer interfaces became more powerful, people began to pay attention to their safety and reliability. With the media's coverage of Musk's BCI project, Neuralink®, brain-computer interfaces have also received more attention from people in related fields.[37] Its ethical and social impacts have also caused more debate. These include data privacy, the possibility of mind control, the consequences of cognitive enhancement, and the ethical issues of accessibility of such cognitive enhancement.[39,40]

Because BCI is a new technology and its impact on human health and development is unknown, it must go through rigorous clinical trials to ensure safety and effectiveness. Regulatory agencies such as the U.S. Food and Drug Administration (FDA) oversee these trials. For example, the FDA has issued guidance on nonclinical trials and study design considerations for BCI devices for patients with paralysis or amputations.[41] This includes the use of encryption and secure data storage protocols to protect neural data from unauthorized access and misuse.

In addition, privacy issues may also become one of the major challenges facing brain-computer interface technology in the future. Since brain-computer interfaces can directly read and analyze EEG signals, this means that highly private information, such as the user's thoughts and emotions, may be intercepted and interpreted. While ensuring the development of technology and the legal, compliant, and reasonable use of information, preventing privacy from being violated is the primary ethical consideration. In addition, fairness issues are crucial. Since BCIs can lead to increased inequalities between social groups- those empowered by brain-computer interfaces and those not empowered- social exclusion and conflict will become more acute and intense. Countries and regulators need to consider how to ensure that everyone has equal opportunities to access and use brain-computer interfaces. At the same time, with the development of brain-computer interface technology, machines with a higher degree of human-machine integration may appear in the future. This means that machines may be able to have a deeper impact on the human brain, leading to illegal interference and control of personal thoughts by machines, causing social unrest.

Future Directions:

It has only been half a century since the brain-computer interface was first proposed. Research on brain-computer interfaces is still in the early stages, and it has broad development prospects. At present, BCIs still have many unsolved difficulties and defects, which require scientists to improve further and clarify future directions.

The development of brain-computer interface hardware is crucial to improving the availability, effectiveness, and accessibility of the technology. The hardware that can be enhanced in future brain-computer interfaces includes electrode design (including materials and structure), the overall appearance of the brain-computer interface, machines with higher computing power, and more advanced signal detection methods. For electrode design, scientists first need to overcome the various defects of current electrode designs mentioned above, such as oxidation resistance and corrosion resistance, durability, and safety. At the same time, in terms of structure, designs with more critical anti-interference capabilities and the ability to collect more brain signals can also significantly improve the performance of brain-computer interfaces. In a recent interview with Noland Arbaugh, the first volunteer to use the brain-computer interface test of Neuralink®, he revealed new difficulties in electrode design. After a period of use of invasive electrodes, the electrodes moved slightly due to the blood flow in the brain. This affected his control of the brain-computer interface and made it impossible for the interface to receive his brain signals accurately. Although Neuralink® has partially improved the problems encountered by Noland Arbaugh through software updates, this also exposed the electrode design as still needing further improvement.[42]

In addition, with continuous development of brain-computer interface design in the future, the overall appearance of the machine will also be an essential consideration. Smaller and more integrated hardware components could make brain-computer interfaces more suitable for everyday use. Stylish designs could attract the public's attention and enable brain-computer interfaces to be more widely disseminated. Moreover, the realization of wireless signal detection technology can promote the development of BCIs to a greater extent. In the future, BCIs are expected to be wireless in design, with small batteries, and can be powered by external power or through energy harvesting technology to meet their power supply needs.[43] This can greatly improve the user's mobility and comfort, allowing them to experience the brain-computer interface without the need for heavy equipment.

As for the software, the most critical and urgently needed part of the brain-computer interface is the decoding of signals. So far, the accuracy of most decoding methods is relatively low. Moreover, the application of these decoding methods usually has considerable limitations. They can only be effectively decoded in specific scenarios and often require a lot of targeted practice to enhance the relevant signals.

In addition, due to individual differences, some models are only effective in specific populations. For example, for patients born without the ability to speak, the model suitable for ordinary people may be seriously affected, and even speech generation may be completely unusable. Therefore, there is an urgent need for a more universal and more accurate decoding model to solve this fundamental problem.[44]

The addition of artificial intelligence (AI), especially deep learning algorithms, has also significantly improved the performance of BCI systems. These AI models can decode complex brain activity more accurately and efficiently. The reliance on more accurate data collection and calibration can be effectively reduced with the continuous improvement of algorithms, such as data enhancement and transfer learning. Classification algorithms, such as support vector machines (SVM), random forests, and convolutional neural networks (CNN), are used to identify and classify patterns in neural data, such as specific motor commands or cognitive states. This dramatically helps brain-computer interfaces convert complex neural signals into understandable outputs that can be acted upon. At the same time, brain-computer interfaces can also make more specific and in-depth analyses of neural signals.[45,46] In the future, machine learning models should be able to adapt to individual users by continuously learning from their neural activity and making specific modifications. This can also significantly improve the accuracy and usability of brain-computer interfaces because neural patterns may vary between individuals and may change over time.

Conclusion

The article reviews the progress over the past exploration of brain-computer interfaces and the challenges that still need to be overcome. Brain-computer interfaces have developed from early theories to today's complex invasive and non-invasive systems. The two invasive electrode types, intracortical and electrocorticographic, are a trade-off between signal quality and safety. Non-invasive systems provide safer solutions, while invasive systems provide higher-resolution neural data at the cost of increased risk.

DOI: 10.36838/v7i4.36

In addition, the emergence of brain-computer interfaces has brought hope to many patients with disabilities or neurological diseases, allowing them to recover some of their physical abilities and return to daily life. At the same time, it has also allowed some game enthusiasts to see the possibility of achieving a more realistic and immersive gaming experience in the future. The application of brain-computer interfaces has made many breakthroughs in the past decade, such as robotic arm control and voice spelling. This has made many people's scientific fantasies no longer just theoretical but have the possibility of actual realization, and these advances highlight their transformative potential.

Despite these advances, many vital challenges currently faced by brain-computer interfaces are also explained in this article. The design and implementation of electrodes remain key obstacles, especially in achieving a balance between invasiveness, signal fidelity, and long-term usability. The development of flexible electrodes and the pursuit of biocompatible and durable materials reflect ongoing efforts to overcome these barriers. However, difficulties in ensuring reliable long-term performance and minimising damage to neural tissue continue to limit the widespread adoption of invasive BCIs. Signal noise and decoding further complicate the effectiveness of BCIs. The neural signals that BCIs rely on are inherently weak and susceptible to interference from various physiological and environmental sources. Effective noise reduction and signal processing techniques are essential to improving the accuracy and reliability of BCIs. The integration of artificial intelligence, particularly deep learning algorithms, offers a promising avenue to improve signal decoding accuracy. However, the challenge remains to develop universally applicable models that work across different users and conditions.

Moreover, as BCI technology advances, ethical considerations and regulatory frameworks are key challenges that cannot be ignored. There is concern that future brain-computer interfaces may access and decode personal neural data, leading to serious privacy issues such as the leakage of personal information and thoughts. In addition, the potential dangers and ethical impacts of using brain-computer interface-based cognitive enhancements, as well as the possible unequal access, pose serious challenges to society and must be addressed through careful regulation and supervision. This article emphasises the need for strong ethical guidelines and regulatory frameworks to ensure responsible and fair development and deployment of BCI.

In the future, the direction of BCI development depends on the continued progress of hardware and software. The development of more sophisticated, user-friendly, and wireless systems can significantly improve the practicality and accessibility of BCI. Similarly, improvements in artificial intelligence and machine learning algorithms can dramatically improve the decoding of neural signals, making BCI more effective and more adaptable to individual needs.

In summary, although BCI has made significant progress, they are still in the early stages of development. There are still technical, ethical, and regulatory challenges on the road to widespread implementation, which require continued research and innovation. Once a mature brain-computer interface becomes a reality, it will bring significant social changes. Although there is still some distance to achieve a perfect brain-computer interface, based on the recent pace of development, widespread use of brain-computer interfaces is expected to become a reality within the next several decades.

Acknowledgments

I am very grateful to my tutor, Marcin Kedziera, for his continuous guidance and help in teaching me how to solve many technical problems and use different query tools to complete my paper. I would also like to thank the Indigo teams, which provided me with the opportunity to finish my essay.

References

1. Wolpaw, J. R.; Millán, J. del R.; Ramsey, N. F. Brain-computer interfaces: Definitions and principles. In *Brain-Computer Interfaces*; Ramsey, N. F., Millán, J. del R., Eds.; Elsevier: 2020; Vol. 168, *Handbook of Clinical Neurology*, pp 15–23. DOI: 10.1016/B978-0-444-63934-9.00002-0.
2. Nicolas-Alonso, L. F.; Gomez-Gil, J. Brain Computer Interfaces, a Review. *Sensors* 2012, *12* (2), 1211–1279. DOI: 10.3390/s120201211.
3. Abdulkader, S. N.; Atia, A.; Mostafa, M.-S. M. Brain computer interfacing: Applications and challenges. *Egypt. Inform. J.* 2015, *16* (2), 213–230. DOI: 10.1016/j.eij.2015.06.002.
4. Wolpaw, J. R.; Bedlack, R. S.; Reda, D. J.; Ringer, R. J.; Banks, P. G.; Vaughan, T. M.; Heckman, S. M.; McCane, L. M.; Carmack, C. S.; Winden, S.; McFarland, D. J.; Sellers, E. W.; Shi, H.; Paine, T.; Higgins, D. S.; Lo, A. C.; Patwa, H. S.; Hill, K. J.; Huang, G. D.; Ruff, R. L. Independent home use of a brain-computer interface by people with amyotrophic lateral sclerosis. *Neurology* 2018, *91* (3), e258–e267. DOI: 10.1212/WNL.0000000000005812.
5. Bockbrader, M. A.; Francisco, G.; Lee, R.; Olson, J.; Solinsky, R.; Boninger, M. L. Brain Computer Interfaces in Rehabilitation Medicine. *PM R* 2018, *10* (9, Supplement 2), S233–S243. DOI: 10.1016/j.pmrj.2018.05.028.
6. Merante, A.; Zhang, Y.; Kumar, S.; Nam, C. S. Brain--Computer Interfaces for Spinal Cord Injury Rehabilitation. In *Neuroergonomics: Principles and Practice*; Nam, C. S., Ed.; Springer International Publishing: 2020; pp 315–328. DOI: 10.1007/978-3-030-34784-0_16.
7. Tudor, M.; Tudor, L.; Tudor, K. I. [Hans Berger (1873-1941)--the history of electroencephalography]. *Acta Med. Croatica* 2005, *59*, 307–313.
8. Walter, W. G.; Cooper, R.; Aldridge, V. J.; McCallum, W. C.; Winter, A. L. Contingent Negative Variation: An Electric Sign of Sensori-Motor Association and Expectancy in the Human Brain. *Nature* 1964, *203*, 380–384.
9. Murthy, V. N.; Fetz, E. E. Coherent 25- to 35-Hz oscillations in the sensorimotor cortex of awake behaving monkeys. *Proc. Natl. Acad. Sci. U.S.A.* 1992, *89* (12), 5670–5674. DOI: 10.1073/pnas.89.12.5670.
10. Vidal, J. J. Toward Direct Brain-Computer Communication. *Annu. Rev. Biophys. Bioeng*. 1973, *2*, 157–180. DOI: 10.1146/annurev.bb.02.060173.001105.
11. Kawala-Sterniuk, A.; Browarska, N.; Al-Bakri, A.; Pelc, M.; Zygarlicki, J.; Sidikova, M.; Martinek, R.; Gorzelanczyk, E. J. Summary of over Fifty Years with Brain-Computer Interfaces—A Review. *Brain Sci*. 2021, *11* (1), 43. DOI: 10.3390/brainsci11010043.

12. National Cancer Institute. Neuron description. 2019. *Anatomy and Physiology* by the US National Cancer Institute's Surveillance, Epidemiology and End Results (SEER) Program. Available online: https://commons.wikimedia.org/wiki/File:Neuron.svg.
13. Squire, L.; Berg, D.; Floyd E. Bloom; Sascha du Lac; Anirvan Ghosh; Nicholas C. Spitzer. *Fundamental Neuroscience*; Elsevier-Academic Press, Cop: Amsterdam; Boston; Paris, 2013.
14. Wu, J. *Introduction to Neural Dynamics and Signal Transmission Delay*. Walter de Gruyter: 2001.
15. He, B. *Neural Engineering*. Springer: 2020.
16. Schalk, G.; Leuthardt, E. C. Brain-Computer Interfaces Using Electrocorticographic Signals. *IEEE Rev. Biomed. Eng*. 2011, *4*, 140–154. DOI: 10.1109/RBME.2011.2172408.
17. Groothuis, J.; Ramsey, N. F.; Ramakers, G. M. J.; van der Plasse, G. Physiological Challenges for Intracortical Electrodes. *Brain Stimul*. 2014, *7* (1), 1–6. DOI: 10.1016/j.brs.2013.07.001.
18. Karumbaiah, L.; Saxena, T.; Carlson, D.; Patil, K.; Patkar, R.; Gaupp, E. A.; Betancur, M.; Stanley, G. B.; Carin, L.; Bellamkonda, R. V. Relationship between intracortical electrode design and chronic recording function. *Biomaterials* 2013, *34* (33), 8061–8074. DOI: 10.1016/j.biomaterials.2013.07.016.
19. Teplan, M. Fundamentals of EEG measurement. *Meas. Sci. Rev*. 2002, *2* (2), 1–11.
20. Sanei, S.; Chambers, J. A. *EEG Signal Processing*. John Wiley & Sons: 2013.
21. Mir, N.; Sarirete, A.; Hejres, J.; Omairi, A. Use of EEG technology with based brain-computer interface to address amyotrophic lateral sclerosis—ALS. In *Research & Innovation Forum 2019: Technology, Innovation, Education, and their Social Impact 1*; Springer: 2019; pp 433–439.
22. Vrba, J.; Robinson, S. E. Signal Processing in Magnetoencephalography. *Methods* 2001, *25* (2), 249–271. DOI: 10.1006/meth.2001.1238.
23. Ferrari, M.; Quaresima, V. A brief review on the history of human functional near-infrared spectroscopy (fNIRS) development and fields of application. *NeuroImage* 2012, *63* (2), 921–935. DOI: 10.1016/j.neuroimage.2012.03.049.
24. Hallett, M. Transcranial Magnetic Stimulation: A Primer. *Neuron* 2007, *55*, 187–199. DOI: 10.1016/j.neuron.2007.06.026.
25. Sriram, K.; Karageorgos, I.; Wen, X.; Veselý, J.; Lindsay, N.; Wu, M.; Khazan, L.; Pothukuchi, R. P.; Manohar, R.; Bhattacharjee, A. HALO: A Hardware–Software Co-Designed Processor for Brain–Computer Interfaces. *IEEE Micro* 2023, *43* (3), 64–72. DOI: 10.1109/MM.2023.3258907.
26. Sriram, K.; Pothukuchi, R. P.; Gerasimiuk, M.; Ugur, M.; Ye, O.; Manohar, R.; Khandelwal, A.; Bhattacharjee, A. SCALO: An Accelerator-Rich Distributed System for Scalable Brain-Computer Interfacing. *Proceedings of the 50th Annual International Symposium on Computer Architecture*; Association for Computing Machinery: 2023; Articleno. 72; pp 20. DOI: 10.1145/3579371.3589107.
27. World Health Organization. *Ageing and Health*. World Health Organization. https://www.who.int/news-room/fact-sheets/detail/ageing-and-health.
28. Ferris, D. P. The Exoskeletons Are Here. *Journal of NeuroEngineering and Rehabilitation* 2009, *6* (1). https://doi.org/10.1186/1743-0003-6-17.
29. Kapsalyamov, A.; Jamwal, P. K.; Hussain, S.; Ghayesh, M. H. State of the Art Lower Limb Robotic Exoskeletons for Elderly Assistance. *IEEE Access* 2019, *7*, 95075–95086. DOI: 10.1109/ACCESS.2019.2928010.
30. Lee, S.-H.; Lee, M.; Lee, S.-W. Neural Decoding of Imagined Speech and Visual Imagery as Intuitive Paradigms for BCI Communication. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 2020, *28* (12), 2647–2659. https://doi.org/10.1109/tnsre.2020.3040289.
31. Wandelt, S. K.; Bjånes, D. A.; Pejsa, K.; Lee, B.; Liu, C.; Andersen, R. A. Representation of internal speech by single neurons in human supramarginal gyrus. *Nat. Hum Behav*. 2024, *8* (6), 1136–1149. DOI: 10.1038/s41562-024-01867-y.
32. Prapas, G.; Glavas, K.; Tzimourta, K. D.; Tzallas, A. T.; Tsipouras, M. G. Mind the Move: Developing a Brain-Computer Interface Game with Left-Right Motor Imagery. *Information* 2023, *14* (7), 354. DOI: 10.3390/info14070354.
33. Tang, H.; Dai, M.; Du, X.; Hung, J.-L.; Li, H. An EEG study on college students' attention levels in a blended computer science class. *Innov. Educ. Teach. Int.* 2024, *61* (4), 789–801. DOI: 10.1080/14703297.2023.2166562.
34. Boddu, V.; Kodali, P. PSO-based optimization for EEG data and SVM for efficient deceit identification. *Soft Comput*. 2023, *27*, 9835–9843. DOI: 10.1007/s00500-023-08476-3.
35. Yuan, H.; Li, Y.; Yang, J.; Li, H.; Yang, Q.; Guo, C.; Zhu, S.; Shu, X. State of the Art of Non-Invasive Electrode Materials for Brain–Computer Interface. *Micromachines* 2021, *12* (12), 1521. DOI: 10.3390/mi12121521.
36. He, G.; Dong, X.; Qi, M. From the perspective of material science: a review of flexible electrodes for brain-computer interface. *Mater. Res. Express* 2020, *7* (10), 102001. DOI: 10.1088/2053-1591/abb857.
37. Rashid, M.; Sulaiman, N.; Abdul Majeed, A. P. P.; Musa, R. M.; Ab. Nasir, A. F.; Bari, B. S.; Khatun, S. Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface: A Comprehensive Review. *Front. Neurorobot.* 2020, *14*, DOI: 10.3389/fnbot.2020.00025.
38. Coin, A.; Mulder, M.; Dubljević, V. Ethical aspects of BCI technology: What is the state of the art? *Philosophies* 2020, *5* (4), 31. DOI: 10.3390/philosophies5040031.
39. Rainey, S.; Martin, S.; Christen, A.; Mégevand, P.; Fourneret, E. Brain recording, mind-reading, and neurotechnology: Ethical issues from consumer devices to brain-based speech decoding. *Sci. Eng. Ethics* 2020, *26*, 2295–2311. DOI: 10.1007/s11948-020-00259-8.
40. Burwell, S.; Sample, M.; Racine, E. Ethical aspects of brain computer interfaces: A scoping review. *BMC Med. Ethics* 2017, *18*, DOI: 10.1186/s12910-017-0220-y.
41. Health, C. D. R. Implanted Brain-Computer Interface (BCI) Devices for Patients with Paralysis or Amputation - Non-clinical Testing and Clinical Considerations. U.S. Food and Drug Administration: 2021.
42. PowerfulJRE. Joe Rogan Experience #2167 - Noland Arbaugh. YouTube: 2024.
43. Even-Chen, N.; Muratore, D. G.; Stavisky, S. D.; Hochberg, L. R.; Henderson, J. M.; Murmann, B.; Shenoy, K. V. Power-saving design opportunities for wireless intracortical brain–computer interfaces. *Nat. Biomed. Eng.* 2020, *4* (10), 984–996. DOI: 10.1038/s41551-020-0595-9.
44. Luo, S.; Rabbani, Q.; Crone, N. E. Brain-Computer Interface: Applications to Speech Decoding and Synthesis to Augment Communication. *Neurotherapeutics* 2022, *19* (1), 263–273. DOI: 10.1007/s13311-022-01190-2.
45. Albahri, A. S.; Al-Qaysi, Z. T.; Alzubaidi, L.; Alnoor, A.; Albahri, O. S.; Alamoodi, A. H.; Bakar, A. A. A Systematic Review of Using Deep Learning Technology in the Steady-State Visually Evoked Potential-Based Brain-Computer Interface Applications: Current Trends and Future Trust Methodology. *Int. J. Telemed. Appl*. 2023, *7741735*, DOI: 10.1155/2023/7741735.
46. Gemein, L. A. W.; Schirrmeister, R. T.; Chrabąszcz, P.; Wilson, D.; Boedecker, J.; Schulze-Bonhage, A.; Hutter, F.; Ball, T. Ma-

 DOI: 10.36838/v7i4.36

chine-learning-based diagnostics of EEG pathology. *NeuroImage* 2020, *220*, 117021. DOI: 10.1016/j.neuroimage.2020.117021.

Authors

Honglin Zheng is a junior at Furen International School, Singapore. He is passionate about mathematics, physics, and neuroscience and is committed to studying engineering further in college in the future.