



BRAIN MACHINE INTERFACE: AN ADVANCED HUMAN BEING

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ABSTRACT

In this world many people have their perception towards external stimuli, it's very tough for an individual to say about their sense of smell, taste, hearing, etc. Most of the people who are suffering from the neurological disorders like Parkinson's disease, Epilepsy, Quadriplegia, and many other brain diseases. What if we cure a person just by controlling the neural activity in the Brain? Well, to put a permanent solution for these all the **BMI (Brain Machine Interface)** has come into existence. The main function of the BMI is to convert the neural signals into commands to produce the desired outcome, the impulses (action potentials) from the neurons are captured by the electrodes placed in the brain and are converted into commands by using the EEG (Electroencephalography), ECOG (Electrocorticography) and the Neuralink App designed in such a way that, it assists in connecting with nearby devices. There are many added advantages such as enhancing the cognitive and physiological abilities of a person, creating a permanent solution for dementia, and surviving the upcoming generations with upgraded versions of artificial intelligence, also there are many challenges such as privacy issues, and security for the information are faced by this chip. This article emphasizes an overall review of the **Brain-Machine Interface (BMI)**. What this is made up of? How does it function? Is it compatible with humans or not? What are the applications and limitations?

KEYWORDS: BMI, BCI, CBI, BBI, Transhumanism, ethical issues, sensory function, motor function, neurology, synapses.

INTRODUCTION

According to the latest survey reports released by the WHO says that on an average 1.3 billion people experience significant disability. This represents 16% of the world's population, or 1 in 6 of us. It's indeed saddening that many people struggle to carry out their daily tasks because of disabilities. So, what if we can treat them to gain their access once gain. What if we say that just by thinking you can accomplish your work? What if you can communicate with any electronic device without any physical movement? what if we can download and restore tremendous of information at a single go. What if we treat psychological disable person such as Hallucinations or Dementia without any medication? Have you ever evoked your dream after awakening?

Have you wondered or dumbstruck what's all this, what is this article says about? Well, to put all the questions apart. Presenting the one of the most inquisitive and most widely reached topic is (BMI) Brain Machine Interface or Brain-Computer Interface (BCI). This article let you know all about the How is Brain Computer Interface has

been constructed. It's Applications, Challenges, N1 chip, Future prospects and Transhumanism.

What is BCI?

The field of Brain-Computer Interface (BCI) technology has emerged as a potent tool for communication between users and systems, offering the ability to issue commands and complete interactions without the need for external devices or muscle intervention.^[55] BCIs have primarily focused on creating assistive devices to restore movement abilities for physically challenged or locked-in users, as well as replacing lost motor functionality.^[46]^[3] However, recent research has expanded the scope of BCIs to include non-medical applications, particularly targeting normal individuals as a novel input device and exploring hands-free applications.^[55]^[46] They can even make existing computer systems more accurate in various fields like industry, education, and entertainment.

History of the Brain Machine Interface

1. 1960s: Early attempts to translate neuronal activity into commands for external devices were conducted

on monkeys in the 1960s.^[1]

2. **1960s-1970s:** During this period, the concept of Brain-Machine Interfaces (BMIs) began to take shape.
3. **1970:** The term "brain-computer interface" (BCI) emerged in the 1970s.^[1] electroencephalography (EEG) was used to directly link brain activity with computers.^[11]
4. **Late 1970s:** Human BMI research started to gain traction, although progress was limited by technological constraints and a lack of understanding of brain physiology.

Kuhlman had demonstrated mu rhythm can be enhanced by EEG feedback training.

The potential of using signals from single cortical neurons to control external devices, marking the early stages of BMI development.^[13]

5. **1973: Vidal** proposed the Brain-Computer Interface Project, which aimed to establish a communication channel between the brain and a computer. Initial experiments with monkeys showed that signals from single cortical neuron could be used to control a meterneedle, laying the groundwork for human BMI research.^[57,3]
6. **1980s:** There are significant advancements were made in BMI research. Researchers like Elbert et al. showed that biofeedback sessions of slow cortical potentials in EEG activity could be used to **control movements on a screen.**^[7]

Farwell and Donchin demonstrated the use of the **P300 event-related potential for spelling words on a computer screen**, showcasing the potential of brain signals for communication and control.^[12]

7. **Late 1980s-1990s:** During this period, researchers delved deeper into sensorimotor rhythms recorded over the sensorimotor cortex.^[14]

The **mu and beta rhythms** were found to be associated with movement or movement imagery. Volunteers were trained to control sensorimotor rhythm amplitudes to accurately move cursors on computer screens, demonstrating the feasibility of using brain signals for device control.^{[62],[63],[64]}

8. **2006:** A significant breakthrough occurred in 2006 when a microelectrode array was implanted in the primary motor cortex of a patient with tetraplegia. This implant allowed the patient to control various devices using **brain signals, such as opening emails, operating a television, and using a robotic arm.**^[25] This marked a major milestone in BMI research, showcasing the potential for individuals with disabilities to interact with the world through brain signals.
9. **2008:** Monkey has controlled the anthropomorphic manipulator.^[56]
10. **2011:** In this year Krusienski and Shih displayed recording of the signals from the brain's cortical surface (ECOG) are translated by using the BCI.^[32]
11. **2012:** Reach and grasp tasks were performed by people with tetraplegia using a neuralgy controlled robotic arm.^[24]

12. **2013:** A brain-machine interface enabled bimanual arm movements in monkeys.^[28]
13. **2014:** Research focused on restoring natural sensory feedback in real-time bidirectional hand prostheses.^[47]
14. **2018:** An optoelectronic system for brain neuronal network stimulation was developed.^[37]
15. **2024:** On January 30th Elon Musk's Neuralink implants brain chip in first human.

BCI Components

A Brain-Computer Interface (BCI) serves the function of discerning and quantifying attributes of brain signals indicative of the user's intentions. These signals are promptly converted into commands for devices, enabling the fulfillment of the user's wishes. A standard BCI system consists of four sequential components: signal acquisition, feature extraction, feature translation, and device output.^[60] These components operate under the guidance of an operational protocol, which dictates the initiation and timing of operations, the intricacies of signal processing, the format of device commands, and the monitoring of performance. A well-constructed operational protocol allows a BCI system to be adaptable, addressing the specific needs of individual users.

1. Signal Acquisition

Signal acquisition encompasses capturing brain signals using specialized sensor modalities, like scalp or intracranial electrodes for electrophysiological activity or fMRI for metabolic activity. These signals are amplified to suitable levels for electronic processing and may undergo filtration to eliminate electrical noise or undesired signal characteristics, such as 60-Hz power line interference. After amplification and potential filtration, the signals are digitized and transmitted to a computer for subsequent processing and analysis.

2. Feature Extraction

Feature extraction entails analyzing digital signals to differentiate relevant signal characteristics, particularly those associated with the user's intentions, from irrelevant content. These pertinent features are then condensed into a format suitable for translation into output commands. Ideally, these features should demonstrate strong correlations with the user's intent.

In contemporary Brain-Computer Interface (BCI) systems, commonly extracted signal features include time-triggered EEG or ECoG response amplitudes and latencies, power within specific EEG or ECoG frequency bands, or firing rates of individual cortical neurons. Signal features exhibiting transient or oscillatory brain activity often hold the most relevance. To ensure precision in measuring brain signal features, environmental artifacts and physiological artifacts such as electromyographic signals are either avoided or eliminated from the data.

3. Feature Translation

The feature translation process involves transferring the extracted signal features to a specialized algorithm, which then converts these features into commands suitable for controlling the output device, effectively carrying out the user's intentions. For example, a decrease in power within a specific frequency band might trigger the upward movement of a computer cursor, while the identification of a P300 potential could lead to the selection of the corresponding letter.

A pivotal aspect of the translation algorithm lies in its adaptability and dynamic nature. It should be able to accommodate spontaneous alterations in the signal features and adjust to learned changes over time. Moreover, the algorithm must ensure that the entire range of potential feature values corresponds to the complete array of control functionalities provided by the output device.

4. Device Output

The commands produced by the feature translation algorithm are employed to govern the external device, facilitating a range of functions such as selecting letters, manipulating cursors, or operating robotic arms. By engaging with the device, the user receives feedback, thus closing the control loop.

Types of Neural Interfaces

There are different types of the Brain signal recordings or Electrophysiological BCI that are used in the system, studying these assist us in understanding the Neuralink approach to build its brain chip. Well, there are two main categories of BMIs: Noninvasive and Invasive Approaches.

Non-Invasive Approach: An interface has been developed by placing an electronic device outside the body and able to monitor millions of neurons but the signals are frequently distorted and nonspecific.^[9]

Invasive Approach: It is a type of interface where the electrodes are placed inside the skull, directly on the surface of the cortex but with poor or only certain thousands of neurons activity has been monitored.^[9]

Neural interfaces can involve recording or stimulating activities

The process of **recording** the information from brain signals and interprets them these types of Interfaces is referred as **BCI (Brain to Computer Interface)** and the process of communicating by **stimulating** the signals or control the brain is referred as **CBI (Computer to Brain Interface)**.

Usually, Neural Interfaces have been sub-divided: they are.

Invasive

- **ECOG** (Electrocorticography) and

- **Intracortical**.^[52]

Non-Invasive

- **EEG** (Electroencephalogram)
- **MEG** (Magnetoencephalography),
- **fMRI** (Functional Magnetic Resonance Imaging),
- **fNIRS** (Functional Near-Infrared Spectroscopy).^[52]
- **TMS** (Transcranial Magnetic Stimulation)
- **tDCS** (Transcranial Direct Current Stimulation).^[54]

Invasive

1. Electrocorticography (ECoG)

ECoG is a recording method involving implanting electrode grids or strips over the cortex surface through surgery, **as depicted in Fig. 1.**^[48] It records neuronal electrical activity with higher spatial resolution and signal amplitude compared to non-invasive techniques like EEG^[61] and^[40], which considers the number of electrodes as a measure of invasiveness.

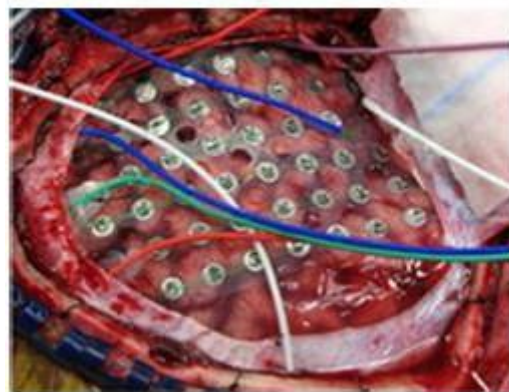


Figure 1: ECoG acquisition.

Advantages and Applications of ECoG: ECoG strikes a balance between invasiveness, accuracy, and safety. It offers better amplitude signals less affected by noise from muscle engagement, making it suitable for seizure localization.^[19] ECoG has been utilized in various studies for motor tasks and speech process classification, such as predicting kinematic parameters for finger flexion^[8] and distinguishing motor-imagery task pairs.^[23]

ECoG in Speech and Language Processing: ECoG has proven beneficial in speech and language processing, particularly when animal models are not applicable. **It has analyzed** the feasibility of decoding semantic information associated with different picture categories using ECoG signals during language-related tasks like picture naming. These insights highlight the versatility and effectiveness of ECoG in diverse applications, ranging from medical diagnostics like seizure localization to advanced tasks in motor control and speech processing.^[58]

2. Intracortical Acquisition Technique

Intracortical acquisition is the most invasive method, involving implantation under the cortex surface of the brain, **as depicted in Fig. 2.**^[26] It can utilize single

electrodes or arrays to measure action signals from individual neurons, providing high spatial resolution for source localization. However, it may face challenges such as long-term signal variability due to neuronal cell death or tissue resistance, and potential noise effects from additional stimuli.^[22]

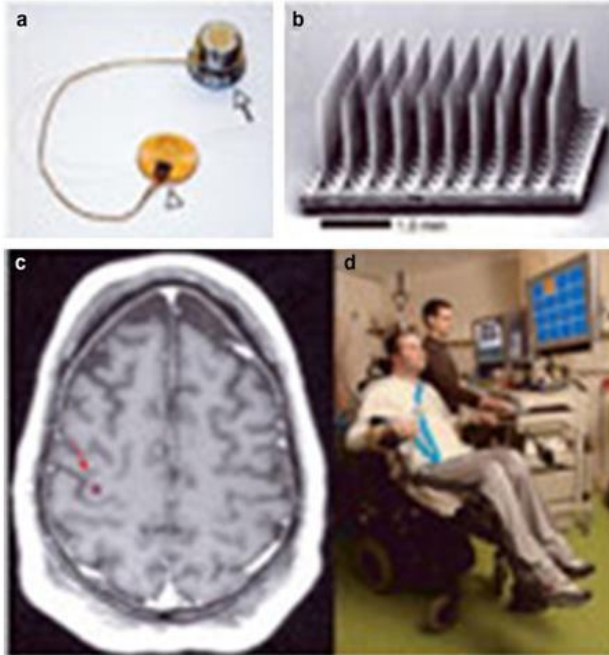


Figure 2: Intracortical acquisition.

BCI Research with Animals: Monkeys and rats have been extensively used in BCI research employing intracortical invasive acquisition. Monkeys were trained to control cursors and brain-controlled robot arms, aiding in movement intention estimation and adaptive movement prediction algorithms.^[40]

BCI Studies with Human Subjects: Limited studies with human subjects using invasive recording techniques have been conducted, primarily with severely disabled individuals such as those with Amyotrophic Lateral Sclerosis (ALS). One study involved an ALS patient controlling a computer cursor after implanting a single electrode into the motor cortex.^[40]

Electrode Number and Classification Accuracy: Actually this has aimed to demonstrate that classification accuracy increases with a higher number of electrodes.^[50] Conversely, other research efforts focused on reducing the number of electrodes to decrease feature size or improve user acceptability.^{[36][31][59]}

This highlights the challenges and potentials of intracortical acquisition techniques in BCI research, including both animal and human studies, with a focus on improving accuracy and user experience through electrode optimization.

Non-Invasive

1. Electroencephalogram (EEG)

EEG records electrical activity along the scalp, capturing voltage fluctuations related to brain neurotransmission. It is user-friendly, portable, and cost-effective, offering high temporal resolution but lower signal-to-noise and spatial resolution compared to other methods.^[17]

Enhancing EEG Spatial Resolution: Solutions for improving EEG spatial resolution include using more electrodes (up to 256) and an international electrode positioning system that optimizes electrode distance relative to scalp diameter.^[3] The electrode assignment demonstrated in **Fig. 3**.^[18]

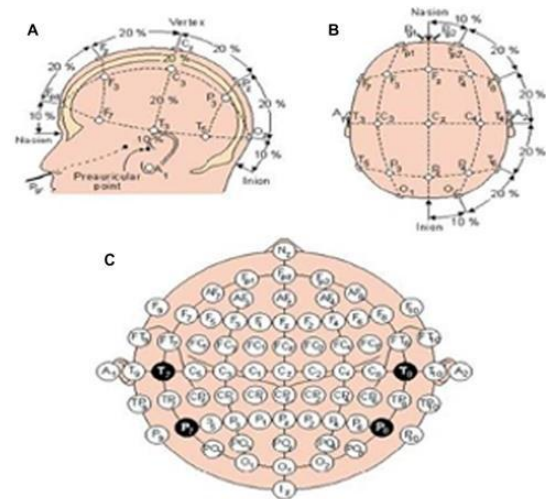


Figure 3: EEG Spatial Resolution.

Alternative EEG Acquisition Methods: Some alternatives to traditional EEG systems include less obtrusive and highly portable options like NeuroSky and Emotiv. There are also innovative methods such as in-the-ear EEG recording, which offers comfort, robustness against electromagnetic interference, and fixed electrode positioning.^[27,35]

BCI Applications: Research focuses on reducing electrode count while maintaining signal quality, especially for discriminating various actions like mental tasks, motor actions, and even imagined actions like writing. Studies also explore using EEG and ECoG signals for motor action classification in both paralyzed and non-paralyzed individuals^[23], with speech presence having minimal impact on accuracy.^{[42][20]}

2. Functional Magnetic Resonance Imaging (fMRI)

fMRI is a technique that detects changes in blood flow related to neural activity in the brain, as depicted in **Fig. 4**.^[51] It maps brain activities to corresponding brain areas, known as the source localization problem, by measuring increases in blood flow associated with brain usage.^[2]



Figure 4: fMRI.

Blood-Oxygen-Level-Dependent (BOLD) Contrast: fMRI relies on BOLD contrast, which is sensitive to the hemodynamic response. The intensities of BOLD contrast reflect changes in deoxyhemoglobin concentration in brain tissue, providing insights into neural activity.^[2]

Spatial Resolution and Information Capture: Although fMRI has low temporal resolution, it offers high spatial resolution and captures information from deep brain regions inaccessible to electrical or magnetic measuring methods.^[22]

3. Functional Near-Infrared Spectroscopy (fNIRS)
fNIRS is a noninvasive technique that measures blood dynamics in the brain to detect neuronal activity. It utilizes near-infrared light to assess blood flow.^[15] The method offers high spatial resolution signals but may have lower temporal resolution compared to electromagnetic signal-based recordings.^[22]

Advantages and Practical Use: fNIRS, as depicted in Fig. 5^[16], has the advantage of being portable and less expensive than fMRI. However, it provides less imaging capabilities compared to fMRI. These advantages position fNIRS as a viable alternative for clinical studies and possibly for practical use.^[22]

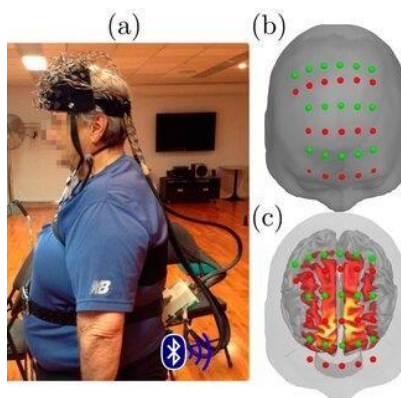


Figure 5: fNIRS.

Transcranial Magnetic Stimulation (TMS) and Transcranial Direct Current Stimulation (tDCS) TMS involves producing a changing magnetic field with a coil

close to the scalp, which can activate or disrupt brain activity, aiding in understanding the role of different brain areas. TMS is also effective in treating drug-resistant depression.^[54]

tDCS uses electrodes placed on the head to deliver constant and direct low current impulses. It has been used to treat depression and pain and is being explored for cognitive enhancement and movement improvement.^[54]

Neuralink Approach

1. Ultra-fine Polymer Probes: Neuralink's neural probes utilize biocompatible thin film materials, featuring a thin film array comprising up to 96 threads with 32 independent electrodes per thread, amounting to a total of 3072 electrode contacts.^[9] The threads have a nominal thickness of 4-6 μm , including insulation and conductor layers, and a length of about 20 mm. Surface modifications aim to reduce impedance and enhance charge-carrying capacity. The packaging process involves a novel alignment and flip-chip bonding method, resulting in a compact package measuring $23 \times 18.5 \text{ mm}^2$.^[9]

2. Neurosurgical Robot: Addressing the challenge posed by the low bending stiffness of electrode probes, Neuralink has developed a neurosurgical robot capable of rapidly and reliably inserting flexible probes to record brain activity across scattered regions.^[9] Custom software facilitates the planning of insertion paths to avoid vasculature. The robot's insertion head includes a quick-swappable "needle-pincher" assembly designed to support and guide the probes during insertion. With the ability to insert up to 192 electrodes per minute, this robotic approach offers efficiency and scalability.^[9]

3. Electronics: Neuralink addresses the technical challenges of recording from numerous electrode sites by integrating the signal amplification and digitization stack within the array assembly.^[9] This recording stack amplifies neural signals, filters out-of-band noise, digitizes the signals, and streams them for real-time processing. Neuralink has developed a custom application-specific integrated circuit (ASIC) containing amplifiers, on-chip analog-to-digital converters (ADCs), and control circuitry for serializing digitized outputs. An Ethernet-connected base station facilitates data stream conversion for real-time data visualization.^[9]

4. Electrophysiology: Digitized signals undergo real-time processing to identify action potentials (spikes)^[9]. Neuralink employs custom online spike-detection software and optimizes spike detection parameters to enhance decoding efficacy.^[9]

Therapeutical Applications

Especially, the BCI has built in such a way that it has wide range of applications for any agedgroups.

1. Paralyzed condition (Quadriplegia)

A person has the capability to respond to the external stimuli by sending the sensory information to Central

Nervous System or to the Peripheral Nervous System to interpret the stimuli and produce the motor response as an outcome. However, in case of the Quadriplegia, the sensory information has sent to brain as usually, to interpret the stimuli and the signals from the CNS will reach to respective organ either it could be hand or leg etc. but fails to perform its action.

In such case it is usually carried out by the N1 chip, where the motor function is accomplished by sending the signals to nearest electronic device such as controlling the IOS device, keyboard and mouse just by thinking to it.^{[9][41]}

2. Epilepsy and Parkinson's Disease

In generally, the Deep Brain Stimulation is used to treat the Parkinson's disease it is usually placed inside the body. There is surgery performed, to place the thin electrode wire in the brain. In addition to that we also need to implant an Impulse generator battery (IPG) under the collarbone.

Whereas, the Karageorgos et al. introduced Epilepsy HALO (Hardware Architecture for Low-Power BCI) is used for recording and processing purpose.^[29]

Neuronal signals are analyzed to predict seizures, and when increased brain excitation is detected, inhibitory synapses are needed to regulate neuronal activity.^[39] BCIs can electrically stimulate neurons to mitigate seizure severity, but the time between seizure onset and stimulation must be very short, typically tens of milliseconds. Safe and chronic implantation of BCIs requires low-power hardware. HALO improves upon previous approaches by offering higher-bandwidth real-time brain communication with low power consumption.^[29]

3. Depression and Brain Diseases

When a person who has gone into depression, usually consumes to have the Anti- Depression medication. Where that particular medication could impact the whole body, such as decreasing of libido and abnormal weight gaining. By using the BMI, it is possible to show the anti-depression action to that particular part of the brain where it is need to show.^[54] If there is any Neurological Disorders of brain, synaptic communication is dysfunctional in such particular places the BMI usually interpret the signals of it assist in communication.^[39]

4. Reading of thoughts and Emotions

What if we know what the other person is thinking about us? Usually, it can be done only by few great mind readers or in few sciences' fiction films but in this case, we have the possibility of knowing others thoughts and Emotions. Well, 70% of the emotions can be detected accurately, by the use of mathematical framework.^[10] There are few experiments that have been conducted, among them one of the best laws, is **The Bayer's law**: It is a study where the volunteer's brain activity has been

recorded and sent to computer as an output by using the (**functional magnetic resonance imaging**) that shows the letters of volunteers that has seen before on handwritten.^[10]

5. Learning and Enhancing

When a brain is the resting phase it defines about the age, mental disorders, and cognitive capability.^[38] By using the BMI, it is possible to control of brain activity patterns corresponding to specific information. This can lead to therapies for psychiatric disorders and enhanced cognitive abilities. The technology for unconscious control of brain activity patterns is expected to become available in cheaper and lighter devices such as EEG and near infrared spectroscopy.^[38] External interfaces, such as headsets using transcranial direct current stimulation (tDCS), are increasingly utilized to enhance memory and concentration. tDCS headsets have shown potential to improve memory, particularly in older individuals, and enhance mental skills. Military experiments suggest that tDCS can sharpen mental skills and enhance physical and mental performance, such as improving the peak performance of cyclists.^[54]

6. Brain to Brain interfaces for communication

Well, there are many approaches to explain the Brain-to-Brain interfaces for communication: they are.

Min's Approach: Brain-to-Brain Interface (BBI) using BCIs and Low-Intensity Focused-Ultrasound (LIFU). Min proposed using BCIs and low-intensity focused- ultrasound (LIFU) sonication to establish a brain-to-brain interface (BBI), allowing two individual brains to communicate by sending signals through computers. This approach aims to enable a wide range of mental communication between individuals.^[4]

Yoo et al.'s Experiment: Functional Links between Human and Rat Brains. Yoo et al. established functional links between a human and a rat brain using transcranial focused ultrasound (FUS) to modulate neural activity and noninvasive BCI techniques such as EEG acquisition and signal processing. By combining these technologies, a brain- to-brain interface (BBI) was created, allowing a human volunteer to move a rat's tail solely by thought, achieving about 94% accuracy.^[49]

Rao et al.'s Experiment: Direct Brain-to-Brain Interface (BBI) in Humans. Rao et al. presented a direct brain-to-brain interface (BBI) in humans, demonstrated through a computer game requiring cooperation between two individuals using BBI communication. The setup involved noninvasive EEG recording of the sender's brain signal and noninvasive transcranial magnetic stimulation (TMS) for stimulating the receiver's brain. During trials, the sender conveyed the intent to fire a cannon in the game through right-hand motor imagery, triggering a TMS pulse to the receiver's brain, resulting in firing the cannon. Although rudimentary, this experiment showed evidence of

information transmission from one human brain to another, serving as a proof of concept for human control via BBI communication.^[45]

Future Possibilities and Risks of Brain-Machine Interfaces (BMIs)

1. Potential Benefits of BMIs

- BMIs could offer various benefits, including improved health, memory, concentration, and healthier aging.^[54]

2. New Risks Associated with BMIs

- The adoption of BMIs also introduces new risks, such as the potential for thoughts or moods to be accessed, raising concerns about privacy and potential misuse.^[54] These may assist people to create global uncertain and geopolitical issues like upsurge of Crime, Terrorism and many other.

3. Access to Thoughts and Mind Control

BMIs could potentially enable telepathic communication and the sharing of sensory experiences among individuals, such as through "neural postcards" conveying sensations like hearing, seeing, and tasting. Virtual experiences, such as enjoying a meal or skydiving, could offer sensations as if they were real.^[54] Within the next 20 years, it may become possible to create visual representations of people's thoughts.^[10]

4. Concerns about Marketing and Political Manipulation

- Access to thoughts could be exploited for marketing purposes, potentially leading to intrusive advertising within individuals' minds. There are concerns about the potential for Orwellian thought policing, where individuals could be penalized for divergent thinking. Privacy issues need to be addressed, as accessing thoughts could enable politicians and companies to recruit individuals to their causes or manipulate public opinion.^[54] Governments may attempt to control and manipulate behavior by directly influencing individuals' brains, potentially through commands or ideological indoctrination.^[1]

5. Consequences of Brain Control - If human brains could be controlled, it would have numerous consequences, such as the potential for selective deactivation of brain functions as a form of punishment. There are dystopian scenarios where brains could be targeted by ransomware, with hackers encrypting brain functions and demanding ransom for decryption.^[54]

6. Potential of Brain-Machine Interfaces (BMIs) for Digital Memory Enhancement

BMIs hold promising opportunities to enhance the brain itself, offering possibilities for improving memory, learning speed, decision-making, and problem-solving without biases. Invasive or noninvasive BMIs could facilitate remembering more information and retaining it more effectively, akin to downloading skills as depicted in the movie "The Matrix". Neural interfaces have the potential to elevate educational achievement levels by assisting students in learning, remembering, and concentrating more effectively. Invasive BMIs may

eventually become integrated into the human body like modern pacemakers. Memory and associated knowledge could be securely backed up on digital devices or uploaded to the cloud, offering the potential for comprehensive memory storage and retrieval.^[54]

Merging Human Intelligence with Artificial Intelligence (AI)

1. Comparison between Brain and Computer

The human brain consists of approximately 86 billion neurons, each capable of making connections with thousands of other neurons via synapses. While computers can perform billions of operations per second, they are typically connected to only a few neighboring units. In contrast, the brain's neurons can communicate with thousands of neighbors despite performing around 1,000 operations per second. Due to these differences, comparing the brain and computer is complex, and much about the human brain remains unknown, including the language of neuronal communication and the brain's capacity to form connections.^[54]

2. Role of Artificial Intelligence (AI) in Brain-Machine Interfaces (BMIs)

Artificial intelligence (AI) plays a crucial role in neural interfaces, enabling the conversion of neural signals into digital data, such as interpreting instructions from the brain to control a prosthetic arm. In the future, a more intricate relationship between BMIs and AI could emerge, with humans and computers perceived as complementary entities. Humans possess decision-making and emotional intelligence, while computers excel at processing large amounts of data rapidly. Many technology experts believe that linking human and artificial intelligence through BMIs could have beneficial impacts. Companies like Neuralink are actively pursuing the goal of connecting human brains with AI.^[54]

3. Necessity of Converging Human and Machine Intelligence

Some experts argue that the convergence of humans with machines could soon become a reality and a necessity, particularly in the era of distractions and information overload. This convergence aims to amplify cognitive capacities by enabling closer collaboration between the human brain and technology.^[11]

4. Long-Term Goals and Ethical Considerations

Elon Musk, the founder of Neuralink, has stated that the company's long-term goal is to achieve "symbiosis with artificial intelligence," which he believes is necessary to compete with increasingly powerful AI and ensure the survival of humanity. Collaborative intelligence between humans and AI could lead to revolutionary applications but also raise significant ethical issues.^[54]

Transhumanism, Brain-Machine Interfaces (BMIs), and Philosophical Issues

1. Challenge to Human Essence

- BMIs challenge the fundamental understanding of what it means to be human, as they have the potential to alter the sense of self.^[53] Distinguishing between enhancement and treatment is difficult and often hinges on defining normality and disease, with debates over whether enhancement constitutes an increase or a reduction in human capabilities.^[6]

2. Transhumanism and Ethical Questions

Transhumanism envisions a world where bodily and cognitive characteristics are enhanced to achieve a post-human stage, raising numerous ethical and philosophical questions about the nature of humanity and the desirability of such transformations.^[34]

Ethical questions include considerations about how humans want to live, whether profound transformations undermine humanity, and whether enhancement promotes a productivist view of human life over qualitative experiences.^[34]

3. The Singularity and AI Threat

- The concept of the singularity, or artificial general intelligence (AGI), raises concerns about the point at which AI can improve itself faster than humans can.^[44]
- While some argue against the likelihood of AGI, many AI experts estimate a significant chance of AGI occurring by 2060.^[33]
- Figures like Stephen Hawking and Elon Musk have cautioned about the potential threats of AI and advocate for BMIs and fusion with AI for the survival of humanity.^[44] These discussions touch on philosophical questions about the emergence or transcendental nature of consciousness.^[44]

4. Potential Impacts on Society and Childhood

- The realization of fusion with AI and the potential threats of AGI raise questions about the future of education, childhood, and social relationships.^[44]
- For instance, if children can instantly download school subjects, it may reshape childhood experiences, education systems, and social interactions.^[44]
- The profound changes anticipated from fusion with machines make it challenging to predict the outcomes with certainty.^[44]

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