CTT
Centre for
Trustworthy
Technology

Rewiring Reality:

How Brain-Computer Interfaces (BCIs) are Redefining Human-Computer Interactions

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About the Centre for Trustworthy Technology

CTT
Centre for Trustworthy Technology

Our vision

Our vision is to empower all through the responsible integration and use of innovative and potentially disruptive technologies.

Our mission

Our mission is to guide organizations in understanding, preparing for, and leveraging transformative and trustworthy technologies, thereby promoting a future where technological innovation benefits all.

Our core values

Our core values include Collaboration, Global inclusivity, Human-Centered outcomes, Being Action-Oriented, Passionate and Committed to Learning & Educating.

Foreword

"Neurotechnology" is one of those powerful words able to trigger sentiments of fear and hope at the same time, and to polarize opinions and attitudes, leaving no one indifferent. While the greatest hopes are generally associated with neurotechnology allowing disable people to e.g. see or walk (again), many applications do not specifically aim to address disabilities. Among them, technologies and devices that can make learning easier or faster, or help meditate, relax or interact in a different way, such as Brain-Computer Interfaces (BCI).

BCI belong to a part of neurotechnology I would define "omnibus", as they are geared towards each and every one of us. The author makes a great job at getting readers acquainted with some of the key facets that BCI may take, without ever remaining too superficial nor becoming too technical. This "primer in BCI" paper fosters a better understanding of these fascinating developments, contributing to inform what has now become an urgent global multi-stakeholder conversation.

Humanity needs to agree on the desirable features of neurotechnology, what we want these technologies to do for humanity. And this cannot be solely or predominantly a technology-centered conversation. That something is technically feasible does not imply that it should be done. I mean, all of us would be technically capable of jumping down from a tall tree, but shall we?

BCI can affect people's identity, autonomy, privacy, sentiments, behaviors and overall wellbeing, among others, and it thus become imperative to decide especially what we do not want these technologies to do or look like, even more if that something hurts (some of) us. At the same time, we need countering the false narrative that holds ethical guardrails to curb or stiffen innovation, technological progress and economic growth and development - a narrative that has already caused non-negligeable mistakes and suffering in the past.

Human rights, human dignity and fundamental freedoms have to be at the center of the development, deployment and use of BCI – and of any other neurotechnology for that matter, especially when coupled with Artificial Intelligence (AI) -, as they have the potential to shake the very foundations of what it means to be a human. "When you add AI, you are putting neurotechnology on steroids" I told the Financial Times in July, when launching UNESCO's "Unveiling the Neurotechnology Landscape: Scientific Advancements, Innovations and Major Trends", and I continue to firmly believe so.

Making BCI safe, secure and trustworthy, as said in the report, is indeed a step in the right direction, but in my mind, it is not enough. We need technologies that are ethical, and that are so by design, with the word ethical that means something very concrete: putting the human, all humans, at the center, also and especially those that societies leave at the margins and that suffer from inequalities and inequities. An example may help. BCI systems helping people learn faster, that respect the characteristics mentioned in the report, could indeed be considered safe, secure and trustworthy. However, if such devices are very costly, and therefore accessible to only a tiny part of the world population (the wealthy one), and if considerations related to e.g. accessibility are not taken into account, such BCI risk widening inequalities. They would be reinforcing the cognitive abilities of those that are already better off (as they have likely gone to better schools, belong to a part of society that enjoys greater opportunities, better health conditions, etc.), while putting others at further disadvantage. Would such BCI be safe, secure and trustworthy? Yes. Would they be ethical? No.

UNESCO, being the institution in charge of social and human sciences and of the ethics of science and new technologies, has recently been tasked by its 194 Member States to work at a Recommendation that would help define the ethical guardrails of neurotechnology. This follows the impressive support received in relation to the adoption and the implementation of our 2021 Recommendation on the Ethics of Artificial Intelligence and makes us confident that change for better is possible. The mandate we received is a testament to the importance of the issue, and mirrors the willingness of countries worldwide to have the important albeit difficult conversation about neurotechnology we need to have, as what is at stake is humanity herself.

Mariagrazia Squicciarini,
Chief Executive Officer,
Social and Human Sciences UNESCO

Introduction

As the scientific community deepens its understanding of neurological function, impressive strides in artificial intelligence (AI) enable researchers to surpass previous limitations in neural data analysis. The simultaneous advancement of the two disciplines is leading innovators to make breakthroughs in radical communication tools called brain-computer interfaces (BCIs). BCIs enable direct interoperability between the neural tissue in live human brains and digital platforms, potentially revolutionizing human experiences by transcending boundaries between physical and virtual experiences. While most use cases are presently focused on healthcare, this tool holds the potential to alter communication, education, and even prevailing social customs.

BCIs comprise a suite of implantable and noninvasive biosensors to collect neural data, and software systems to interpret the data. Some BCI systems include closed feedback loops that initiate deep brain stimulation (DBS)[i] and other stimulation modalities[ii iii]. Functionally, BCI devices enable paraplegics' movement through prosthetic limbs,[iv v vi] allow patients with neurological disorders to communicate,[vii viii] and may inspire novel medical intervention for other neurological diseases, neuro-recovery, and neurorehabilitation[ix x xi xii].

Successful BCI systems must effectively execute four tasks in the realm of biotechnology, AI, and data science:

1. First, biosensors must accurately record signals from the brain. These biosensors may be invasive, such as microelectrode arrays implanted in the brain,[xiii] or non-invasive, such as electroencephalography (EEG)[xiv]. The type of recorded signal is generally dependent on the invasive or non-invasive protocol. Invasive protocols will generally record more intricate data, including spikes from individual neurons or neuronal populations[xv]. Meanwhile, EEG waveforms represent the synchronous activity of large populations of neurons in the cerebral cortex, forming brainwaves (alpha, theta, beta, etc.)[xvi]. The comprehensive understanding of these signals informs the processing and interpretation methodologies that follow.

2. Regardless of approach, biosensors collect considerable noise/interference and require filtering before data processing and analysis[xvii]. For example, artifact rejection procedures must filter out noise from eye blinking,[xviii] muscle contractions,[xix xx] cardiac activity,[xxi xxii] and other biological or non-biological recorded activities[xxiii]. These artifacts are more common for EEG sensors, which record electrical activity farther from cortical tissue[xxiv]. Filtering techniques may include elimination methodologies employing,[xxv] Independent Component Analysis of Classification (ICA),[xxvi xxvii] Support Vector Machines (SVM),[xxviii] Neural Network Regression (NNR),[xxix] Artifact Subspace Reconstruction (ASR),[xxx] and a variety of other algorithms[xxxi xxxii xxxiii].

3. The filtered data is processed and analyzed using AI models. This process may be called feature extraction or signal processing, and its techniques increasingly employ deep learning methods. These methods include Convolutional Neural Networks (CNNs),[xxxiv xxxv xxxvi] Recurrent Neural Networks (RNNs),[xxxvii xxxviii] autoencoders,[xxxix xl] Generative Adversarial Networks (GANs),[xli xlii xliii xliv] transfer learning models,[xlv xlvi xlvii] attention mechanisms,[xlviii xlix l] and hybrid models[li lii] that deploy a combination of these approaches.

4. Bidirectional BCI systems are designed to provide immediate feedback to the user, either through direct stimulation of the brain or through other sensory channels. These systems can be invasive[liii] or non-invasive,[liv lv] and their actions can trigger prosthetic limb movements,[lvi lvii] control external devices[lviii lix], or modulate brain activity patterns to induce neural plasticity[lx lxi].

This point-of-view paper offers foundational information on BCIs, including the technology's origins, history, architecture, and applications. Based on this foundational understanding, the paper will also offer insight into the field's challenges, both existing and anticipated, from technical and ethical perspectives.

BCI Development from Inception to Modern Day

In the 2010 production *Inception*, Leonardo DiCaprio portrays a tech-savvy corporate spy who induces his targets into a dream state before extracting information directly from their minds[lxii]. The targets wore awkward-looking electrode-woven caps that entranced them into brilliantly architected dreams, where every painstaking detail was intended to trick them into believing they were indeed in an alternative reality and not simply dreaming. When this movie aired, the modern-day understanding of BCIs was predominately science fiction perpetuated across late 20th-century cinematic work.

However, in the decade that followed, BCIs would become a cornerstone of national security interests for world leaders,[lxiii lxiv] inspire a fiery competition between notable startups,[lxv] and even inspire a fascination with using the technology for spiritual enhancement[lxvi]. In September 2023, the United Nations Educational, Science, and Cultural Organization (UNESCO)'s International Bioethics Committee published a report to bring awareness to ethical challenges that arise from the use and storage of neural data[lxvii]. The report highlighted concerns over neurotechnology's use in hindering mental integrity, privacy, and freedom. As these highly respected organizations bring awareness and shift their focus to neurotechnology, the industry enters a new era of global media coverage that warrants diligent discussion over its ethical development and adoption.

Despite recent traction in BCI research and products, the industry's conceptualization started as a niche research field. The origins of the technology trace back to 1780 when Luigi Galvani discovered "biological electricity" by rotating generators to contract frog muscles[lxviii]. Around a century later, in 1875, Richard Caton observed recorded electrical potential changes corresponding with peripheral nerve activity and hypothesized that similar electrical principles occur in the brain[lxix]. Using a Thomson reflecting galvanometer image projection, he captured visually evoked electrical potential from exposed cortical tissues in rabbits and monkeys. In 1924, German neuroscientist Hans Berger developed the first electroencephalogram (EEG) device for humans using an Edelmann string galvanometer[lxx]. The initial results from this project proved inconsistent, so Berger developed another EEG system with a more sensitive Siemens double-coil galvanometer with low-impendence surface electrodes. Berger published his first paper on these findings in 1929, when he coined the long-surviving medical terms "alpha" and "beta" waves. Berger didn't stop with non-invasive brain recordings[lxxi] .In 1930, he developed the first human-fitted electrocorticography (ECoG), where the patient underwent neurosurgery to have electrodes fitted on the brain tissue right underneath his scalp[lxxii]. This paper would be the first of Berger's twenty-three publications in BCI research.

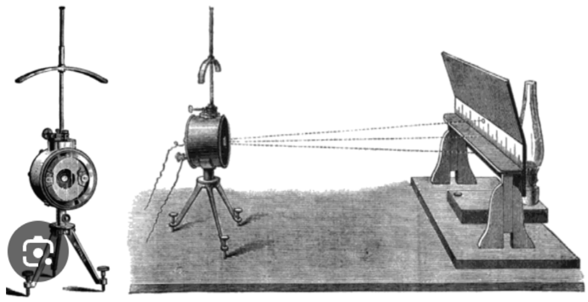

Figure 1 The Thompson Mirror Galvanometer, first conceptualized around 1880, improved the original mirror galvanometer, which used a mirror to deflect light and detect electrical current[lxxiii].

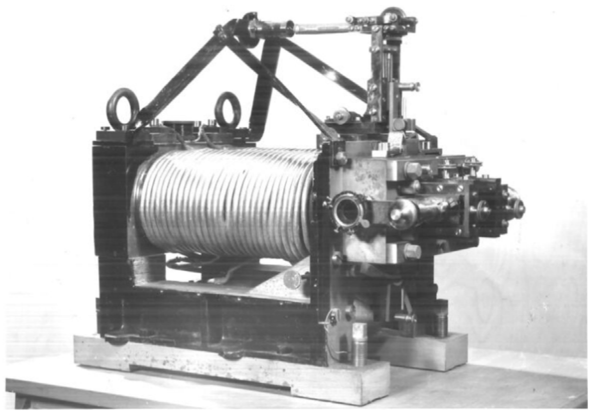

Figure 2 The Edelmann String Galvanometer was conceptualized around 1901-1905. In 1905, it successfully recorded the human heart's electrical activity, paving the way for electrocardiograms (ECGs)[lxxiv].

Most BCI research in the later 20th century was spent building on Berger's earlier work, confirming his findings, and fine-tuning his methodologies to develop tools that were later used for neurophysiology research or to support medical interventions.

Like earlier in the century, BCI research breakthroughs were fueled by improvements to electrical current detection instruments. The conception of the first microelectrode arrays (MEAs) in the 1950s[lxxv] led to C.A. Thomas Jr's 1972 adoption of planar electrodes for recording the electrical activity of cultured cells[lxxvi]. In the 1970s, KD Wise et al. developed silicon-based MEAs[lxxvii] and, in the early 2000s, invented thin film-like electrodes to record neuronal activity in living organisms[lxxviii]. Unlike the electrical activity recording instruments in the first half of the 20th century, the instruments developed in the second half were increasingly bio-compatible, allowing researchers more flexibility and creativity in BCI systems design.

Following a consistent but stagnant volume of BCI research in the late 20th and early 21st centuries, BCI research and BCI-related patent filings grew exponentially starting in the early 2010s[lxxix]. The marked increase in patent filings also corresponds with a noticeable move from predominantly academic BCI research to industry-driven development. The geography of these developments also shifted from Europe to North America and Asia. In the last two decades, the most prolific patent filing BCI research originated in the United States, with China and Korea following behind.

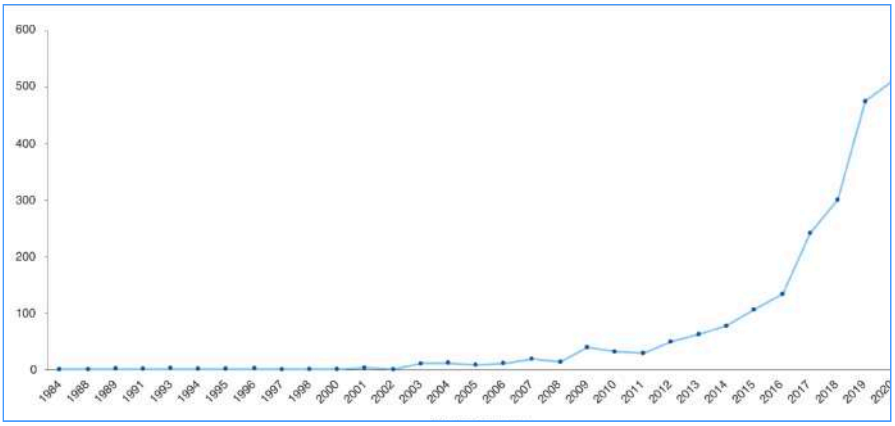

Figure 3 The number of patents filed for BCI-related research experienced significant growth after the early 2010s[lxxx].

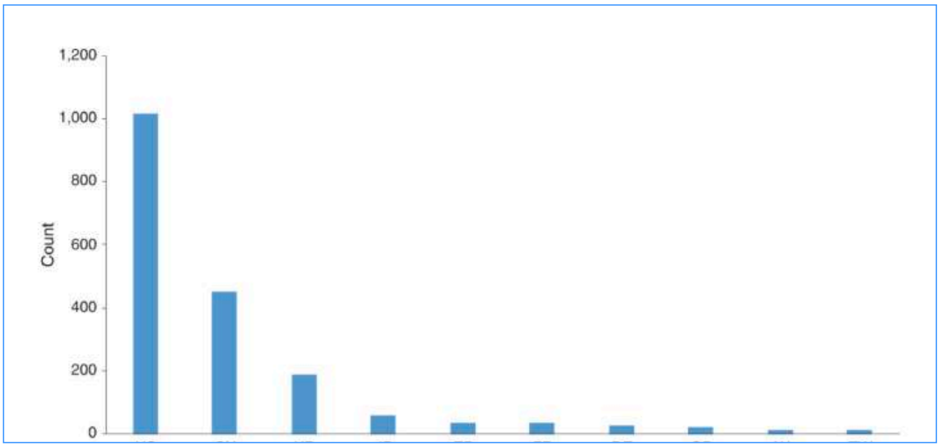

Figure 4 The United States takes a clear lead in BCI-related patent filings, accounting for around double the second most prolific patent filer, China. US - United States, CN - China, KR - South Korea, JP - Japan, EP - Europe, FR - France, DE - Germany, GB - United Kingdom, AU - Australia, TW - Taiwan[lxxxi].

Several prominent BCI startups, from Neuralink to Synchron, were founded in the late 2010s. Their research attracted more popularity in the early 2020s as they moved their first BCI products to initial clinical trials[lxxxii]. Improvements in bioelectrical activity recordings, such as the development of high-density MEAs,[lxxxiii] contributed to the field's growth. However, rapid advancements in other disciplines, including the maturation of increasingly powerful computing hardware, data science, AI, and biomaterials has driven BCI research to achieve an unprecedented level of publication after the 2010s. The next section of this paper will delve into the systems design principles that may inform how these disciplines should converge and the recent breakthroughs that are shaping the architecture of contemporary BCIs.

BCI Architecture: From Hardware to Data Analysis

Systems Design Principles

The full complexity and scope of BCIs are best understood through the technology's methodologies and the opportunities that arise from its proper development. The process of designing, developing, and deploying successful BCI systems is primarily focused on the following key principles:

- **Safety:** Above all else, biomedical technologies must be safe for human users. While safety standards and definitions may differ across national regulators or medical groups, the basic understanding of medical safety is avoiding patient harm. According to the United States Agency for Healthcare Research and Quality, safety is "avoiding harm to patients from the care intended to help them"[lxxxiv]. Given this context, BCI safety considerations are generally a more prevalent concern for implantable devices and stimulators, which carry a risk of injury, both from the design of specific devices and the brain's natural reactions to foreign objects[lxxxv lxxxvi]. The risk of injury should be weighed against patient needs and the likelihood of recovery. These safety practices are also a cause for limiting early BCI research, particularly in invasive forms, to strictly medical applications. It is important to note that while virtually all researchers and regulators agree that safety is the most important principle, the prioritization of the following principles can be fiercely debated. Moreover, the diversity of perspectives often leads to differences in BCI system designs.

- **Resolution:** BCI biosensor efficacy is fundamentally measured through spatial and temporal resolution. Spatial resolution describes the ability of sensors to detect intricate details regarding the locality of the signals' origination. Temporal resolution characterizes the sensors' ability to capture time-variant data. Generally, non-invasive EEG systems have higher temporal resolution but lower spatial resolution. Invasive ECoG systems have both high temporal resolution and high spatial resolution compared to EEG.

- **Effective Feature Extraction:** The raw neural data collected from BCI sensors must be interpreted as relevant information for the end user. The first step in extracting relevant information is to preprocess the signal data by removing artifacts and noise, enhancing the signal-to-noise ratios. Once the data is filtered, researchers extract domain-specific features, such as event-related brain activity (e.g., changes in brainwave frequencies or amplitudes) in response to time-sensitive events or stimuli.

- **Data Model Selection for Interpretation Accuracy:** Appropriate model selection is critical for accurately interpreting the extracted features. When considering data models for specific BCI systems, developers must gauge the signal characteristics (such as the signal-to-noise ratio or stationarity) most critical to their specific objectives, as well as model interpretability, complexity, adaptability, robustness, and computational efficiency.

- **Longevity:** All components in the system architecture, especially hardware, should be relatively durable and appropriate for long-term use. For example, MEA-based brain implants should last at least a few years to minimize the frequency (and, thus, risks) of surgery.

- **User-Centric Design:** Both invasive and non-invasive modalities should prioritize comfort and ease of use for the end user. In consumer markets, BCI devices should not require medical knowledge to operate and should be attractive for frequent use.

Hardware: Capabilities & Limitations

Researchers and engineers will choose specific modalities based on their characteristics and how they align with the unique project requirements and intentions. Generally, BCI sensors are categorized into the following modalities:

Electroencephalography (EEG): The most popular BCI hardware, EEG systems are entirely noninvasive and are offered in various contexts, such as caps, headbands, flexible film, etc. The electrodes are placed on an individual's head and used to measure the electrical potentials generated in the brain via a conducive gel.

EEG systems offer high temporal resolution, with the most advanced devices sensing electrical activity in milliseconds, but their spatial resolution is low relative to more invasive techniques. Therefore, EEG signals are typically frequency bands that measure synchronized waveforms such as delta (0.5-4Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30+ Hz). Because EEG devices are comparatively more accessible than invasive BCIs, they have been applied to various uses, including neurorehabilitation, communication, guided meditation, and environmental control[lxxxvii].

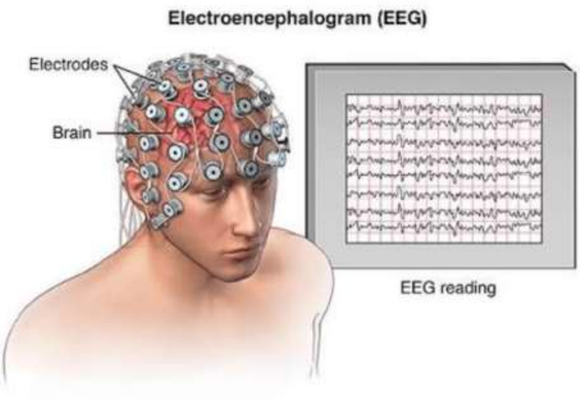

Figure 5 The electrodes placed on top of the man's head record brain activity as brainwaves, which characterize EEG readings[lxxxviii].

» **Meditation & Consumer Markets:** Several meditation companies are developing consumer EEG devices to track brainwaves and offer users feedback on their wakefulness or meditative states. In some cases, the feedback is meant to guide users to their desired mental state, aid with lessening anxiety, improve sleep and generally improve mental health. The mass manufacturing and subsequent commercialization of these products, coupled with their relative ease of use, is an example of successful BCI marketing in consumer markets[lxxxix].

» **Electrocorticography (ECoG):** Also known as intracranial EEG (iEEG), ECoG devices are implanted under the skull and on top of the exposed surface of the brain. The surgical procedure involves removing a part of the skull to expose the surface of the brain's cortex. The electrodes are placed on brain tissue underneath. Because ECoG devices are closer in proximity to neuronal activity and the skull doesn't run interference with the electrodes, ECoG systems likely exhibit higher spatial resolution than EEG devices.[xc xci]

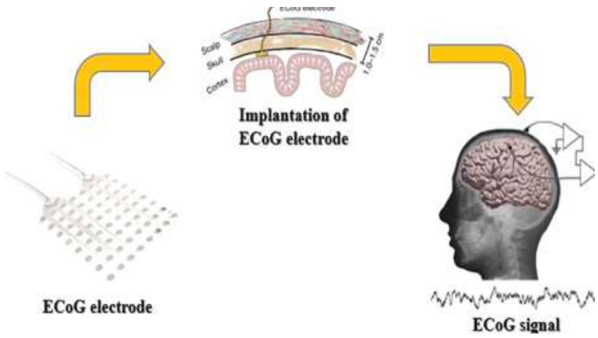

Figure 6 ECoG electrodes, often MEAs, are placed underneath the skull but on the cortical tissue. Because these electrodes are closer to the neuronal activity within critical tissue, they often present better spatial resolution than non-invasive BCI systems[xcii].

» **Intracranial Devices:** Unlike ECoG devices, which record from the surface of brain tissue, intracranial devices are implanted in brain tissue, such as the cortex and other brain structures[xciii]. Intracranial devices are generally intracortical devices, such as MEAs implanted into the cortex to record neuron-level activity or depth electrodes implanted in the hippocampus or amygdala to capture local field potentials (LFPs) [xciv]. Because intracranial devices are closer in proximity to neuronal activity than ECoG or EEG devices, they will generally offer higher spatial and temporal resolution.

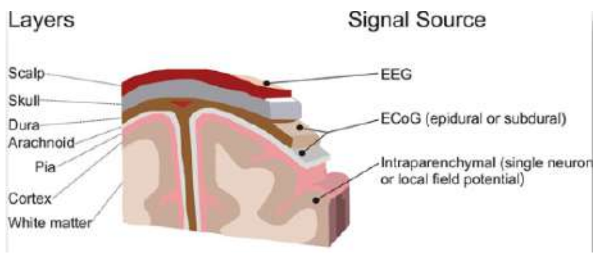

Figure 7 Intracranial devices, or intraparenchymal devices, are the most invasive BCI devices as they are implanted directly inside the brain tissue[xcv].

» **Magnetoencephalography (MEG):** Like EEG, MEG is non-invasive. However, unlike EEG, MEG devices measure the magnetic fields generated by the brain's electrical activity instead of the electric activity itself. These devices use superconducting quantum interference devices (SQUIDs) to detect the brain's magnetic fields. Studies suggest that MEG devices have excellent temporal resolution and may offer better spatial resolutions than EEG[xcvi]. Clinically, MEG can diagnose neurological disorders, and it is frequently used in sensory processing, cognitive function analysis, and measuring brain connectivity[xcvii].

BrainGate: BrainGate, once the world's most sophisticated BCI system, was based on an intracranial device that allowed a quadriplegic woman to serve herself coffee[xcviii]. The BrainGate project, which was initiated in the early 2000s, was considered groundbreaking when its 2012 study was credited with demonstrating the effectiveness of using MEA to decode and generate signals to external (in this case, robotic) systems.

Neuralink: The company's 2019 whitepaper describes the implantable device as an intracranial compilation of 96 flexible electrode "threads" that contained around 3,072 electrodes per array[xcix]. The Neuralink chip currently undergoing human clinical trials comprises 64 polymer threads with 1,024 electrodes[c]. Neuralink has consistently conveyed its mission to aid patients with paralysis and other neurological disabilities.

Some neuroimaging devices qualify as BCIs because they allow researchers to visualize neural structures on electronic systems. However, these devices are typically restricted to neuroimaging use in diagnostics and fail to offer the same communication-based functionalities as the other methods mentioned previously.

These devices include:

» **Functional Magnetic Resonance Imaging (fMRI):** fMRI is a non-invasive neuroimaging technique that leverages magnetic fields and radio waves to detect changes in blood oxygenation and flow (the blood-oxygen-level-dependent (BOLD) contrast)[ci]. fMRIs have high spatial resolution but low temporal resolution. Clinically, these devices often aid in studying structural brain abnormalities or serve as presurgical mapping tools[cii].

» **Functional Near-infrared Imaging (fNIR):** fNIRs leverage the absorption of near-infrared light by hemoglobin (HbO) and deoxygenation hemoglobin (HbR) to detect changes in brain activity. Light sources and detectors are placed on the scalp, and neural activity is measured through hemodynamic responses[ciii]. The spatial resolutions of fNIRS systems are lower than those of fMRI systems but higher than those of EEG. It is important to note that fNIRs are typically only applied to cortical activity, as near-infrared light cannot penetrate deeper brain tissues[civ].

» **Positron Emission Tomography (PET):** PET scans adopt radioactive tracers to track metabolic processes in the brain. Specific chemical tracers detect neurotransmitters relevant to pathological processes like amyloid plaques, which are critical in studying Alzheimer's disease[cv]. Spatial and temporal resolution is limited to tracer kinetics, but PET scans are effective and widely used to diagnose and monitor neurological diseases.

AI Models of Neural Data Interpretation

BCI signal processing began as a manual human task until machine learning techniques allowed the automated procedure of separating usable signals from noise. However, most of these algorithms could only extract the data features necessary for a particular task and require a supervised learning approach to classify and identify patterns within the dataset[cvi]. There are two drawbacks to this approach. First, supervised learning methods require a testing and training dataset, where the training data informs patterns acquired from the testing set. However, an individual's brain may not act consistently for a long enough time horizon to detect usable patterns[cvii]. Moreover, each human brain is unique, so each algorithm needs to be re-trained on new subjects or incorrectly assume that the features extracted from one individual are transferable to another[cviii].

As a result, researchers adopted deep learning techniques that could allow models to learn from and adapt to complex datasets. These techniques may be founded on similar supervised learning principles but possess the unique ability to extract data features and identify patterns simultaneously.

These deep learning models include:

- Convolutional Neural Networks (CNNs): Arguably one of the most popular deep learning methods for neural data interpretation, CNNs may analyze complex, high-dimensional data and are relevant in signal preprocessing, data representation, feature learning, and classification[cix cx]. For example, CNNs can decode imagined speech from EEG signals, [cxi cxii] classify motor imagery tasks for controlling prosthetic limbs,[cxiii cxiv] and predict the onset of seizures in epileptic patients,[cxv] among other applications.

- Recurrent Neural Networks (RNNs): RNNs are uniquely designed to handle sequential data with temporal dependencies, making them ideal for content-dependent neural data interpretations[cxvi cxvii]. RNNs are also adept at handling variable data and are adaptable models that can learn from user brain activity[cxviii].

Future Development

Despite the recent improvements to BCI hardware and software systems, the industry has yet to experience significant scientific or technological breakthroughs that transcend the existing limitations and trade-offs between resolution, durability, and safety. Accelerating BCI research requires consequential advancements in microbiology, electrical engineering, signal processing, data science, and AI. For example, the pivotal technologies on the horizon that may materially advance.

BCI research include but are not limited to:

Biomimetics: Biomimetics is the study and application of biology to design bio-compatible and bio-equivalent materials. Advanced biomimetic fibers could enable high-density, minimally invasive, and long-lasting electrode arrays[cxix]. One of the greatest limitations to existing BCI implants is the body's immune response to protect itself from foreign objects and develop scar tissue[cxx]. Over time, the scar tissue dampens signals from the implant[cxxi]. Biomimetic coatings on implantable devices can promote better attachment and integration within and on neural tissue[cxxii].

» Biomimetics for Microelectrode Arrays: Many invasive BCI implants use synthetic MEAs with metallic electrode surfaces deposited on glass, silicon, or other substrates[cxxiii]. However, these materials are known to cause glial-formed scar tissue, reducing the efficacy of the implants' electrophysiological properties and dampening signals over time. In 2023, Nowduri et al. developed a novel nano-structuring method inspired by the organizational structure of natural collagen fibers. When the substrate on the metallic microelectrode surfaces resembled the fibers, there was decreased scar tissue formation and improved spike (neuronal activity) detection, leading to a 22-41% reduction in impedance magnitude[cxxiv].

Li-Fi Wireless Transmission: Integrating high-bandwidth, low-latency wireless standards could enable faster and more efficient transmission, improving temporal resolution. Light Fidelity (Li-Fi) or transmission through infrared LED enables low latency as it has a shorter signal path than RF technologies and does not suffer from electromagnetic interference. Li-Fi may also be more secure than other wireless standards, like the 5G or Bluetooth protocols currently prominent in industry[cxxv]. However, there is a gap in the academic literature on Li-Fi use in BCI, and further research needs to address several theoretical limitations. For example, Li-Fi ranges are confined to a few meters, making long-range BCI use difficult. A rare study employing Li-Fi use in transmitting EEG signals achieved data transmissions of less than 20 inches[cxxvi]. Moreover, while light use on cortical tissue has been studied through optogenetics and other fluorescent imaging, Li-Fi's light penetration depth on cortical tissue has been scarcely studied. It is important to note that while this research area may warrant further exploration, the current literature insufficiently supports the feasibility or practicality of Li-Fi use in BCI development.

Novel Deep Learning Networks, "Few-shot and zero-shot learning": Few-shot and zero-shot learning models only require a small sample size of data points, enabling quicker adaptation to new users or tasks. These methods could decrease the sample size and, thus, the time required for individuals' neural data to learn their unique signal compositions and tailor the interpretations based on a smaller training set[cxxvii].

Novel Deep Learning Network, Neuromorphic Computation: Neuromorphic systems are designed to be highly energy-efficient and emulate the capabilities of biological neural connections, which include high adaptability, parallel processing, and noise resilience. These networks are designed to mimic biological systems, which may theoretically indicate improved compatibility with natural neural signaling systems[cxxviii].

Trustworthy Perspective: BCI Impact & Ethics

Optimistically, BCI research will continue accelerating as multidisciplinary perspectives collaborate to optimize interoperability between biological and computer systems. Therefore, the existing BCI systems operating in 2024 will likely drastically differ from their future form and functionality, which will depend on forthcoming engineering. The future of this industry and how it shapes society rests on a commitment to building trustworthy BCI systems and ecosystems in which these technologies operate.

Identifying Appropriate Use Amidst High Growth & Promising Commercialization

While "appropriate use" of BCIs may not be, and perhaps should not be, restricted to medical use, it should be limited to trustworthy use. The trustworthy use of BCI systems in communication, entertainment, and other activities unrelated to medical assistance should be explored and encouraged. However, a few guided principles to determine the qualifications of trustworthy use are necessary to discourage BCI usage for malicious intent. For example,

» The BCI system should be safe for the user and others. Fundamentally, BCI systems should not be leveraged by a single user (or a group of users) for the malicious intent of harming another person (or group of persons). Referring back to the cinematic piece *Inception* mentioned earlier in the paper, BCI systems should not be purposefully leveraged to manipulate or cause distress to another person.

» The long-term benefits of using the BCI system should exceed the economic costs of acquiring and implementing the system. When BCI systems are leveraged with positive intent, they should be done so only when they resolve or lessen the burden of a problem that cheaper solutions cannot solve.

Challenges Arising from Appropriate Use

The appropriate use of BCI systems still raise technical, ethical, and trustworthy challenges, including:

Wireless Attacks, Neural Hacking, and Neural Ransomware: Most BCI devices are wireless, making them susceptible to eavesdropping, jamming, and data injection attacks. As with any computer system, BCIs are at risk for traditional computer security threats like malware[cxxix]. Many BCI ecosystems may rely on cloud servers[cxxx] and other large data storage infrastructure with inconsistent security.

Privacy and Security: As neurotechnology grows in sophistication, feature extraction techniques could enable the detection of increasingly private data. Given the highly personal and private nature of neural data, both in its raw form and when interpreted as biometric data, data privacy and security management are critical concerns[cxxxi]. Most BCI protocols use traditional encryption methods familiar to most health information systems, but these security interventions may not be sufficient[cxxxii].

Unintended Disclosure and Difficulty in Anonymizing Neural Data: Because researchers cannot selectively dispose of non-pertinent information, private information (and even thoughts or, at the very least, mental state) may be accidentally stored without the user's prior consent. Neural activity is like a "fingerprint" that could be uniquely attributed to individuals[cxxxiii]. While this would require a herculean effort manually, the rise of AI models could supersede the process, leading to concerns regarding the misuse of private and identifiable neural data.

Transparency, Consent, and Autonomy: Transparent safety disclosure to all BCI users, whether referring to the patient or their doctor, is critical to maintaining the integrity of BCIs' use. In other words, BCI designers, developers, and manufacturers should be held to the highest standard of disclosure to ensure unambiguous user consent and autonomy. Therefore, BCI systems should be designed with a systems architecture that allows for the transparent disclosure of medical risks and biometrics data handling.

- The Leggett Case: The autonomy to choose if or when to discontinue the use of BCI systems should be granted to users, but legal and business obstacles may complicate the exercise of this right. Rita Leggett was an Australian woman struggling with epilepsy before she was fitted with a brain implant that predicts forthcoming with seizures. Leggett said that the device changed her life and she felt that she "became one" with her implant. Devastatingly, the implant was forcibly removed from her when the company that developed the device, NeuroVista, went bankrupt in 2013[cxxxiv]. These crushing cases may become more prevalent in the future. These cases, which are arguably human rights issues, will warrant the development and implementation of active policies and frameworks to address these concerns.

Inclusivity & Accessibility: Like most biomedical innovations, BCI systems are expensive, and early iterations of high-quality BCIs will likely be inaccessible[cxxxv, cxxxvi]. Nonetheless, innovators should consider inclusivity and costs as the research matures to allow the technology to become more ubiquitous.

Building Trust through Principled & Solutions-Based Research and Engineering

The trust built between end-users and researchers must translate to engineering for BCI systems to genuinely reflect user values and principles. Engineering solutions, in addition to policy and business prudence, may resolve many of the ethical challenges pertinent to BCI development.

Enhancing end-user engagement throughout the research and development process represents an unconventional yet markedly more effective approach to building enduring trust. Involving end users in R&D would allow users to gain a more intimate understanding of the goals, methods, and potential risks of medical devices, including BCIs[cxxxvii cxxxviii]. Moreover, conducting research outside of traditional lab settings, such as homes, workplaces, and community spaces, may offer researchers valuable insights regarding how their work performs in real life. Collaborative research models, such as participatory design or citizen science initiatives, can also empower end users to contribute actively to the research process[cxxxix]. Ultimately, by prioritizing trust and engaging with end users beyond the confines of a lab, researchers can build better systems that are both scientifically rigorous and socially responsible for the end user.

Emerging engineering solutions, such as Li-Fi mentioned earlier in the paper, or other wireless data transmission protocols such as Quantum Key Distribution (QKD) could theoretically become more secure. than Bluetooth or 5G[cxl cxli cxlii]. However, it is important to note that the security of any wireless communication technology depends on various factors including, but not limited to, implementation and configuration[cxliii]. These wireless transmission protocols have yet to be seriously explored in existing literature and studies, but their promise could make them worthwhile research endeavors in the future. By employing more secure wireless data transmission protocols, BCIs could decrease the likelihood of neuro-hacking and protect against neuro-ransomware. Moreover, computer engineering solutions such as Zero-knowledge proofs (ZKP) or other advanced encryption methods could allow for the computation of specific datasets without storing these sets[cxliv]. These methods could make it possible for neural technologies to compute a subset of data for computation and storage (such as drug history and other health information) while discarding another subset after computation.

Policy Framework Considerations

Beyond trustworthy principled engineering, BCI systems should adhere to robust and comprehensive policy frameworks that guide their technical maturation and execution. The uncertainty surrounding BCIs' future technical design brings unique challenges and opportunities. On one hand, the nascency of the field allows policymakers an opportunity to be proactive in guiding the field's north star, both in engineering and business. Concurrently, the industry's infancy poses a challenge for policymakers, as they struggle to comprehend the potential risks and ramifications in the field. This lack of understanding makes it arduous to determine whether policies are essential for safeguarding the public interest or if they would unnecessarily hinder innovation. Subsequent papers in this POV series will explore the specific policy considerations to guide this discussion.

Conclusion

The significant strides in BCI research offer a glimpse into a future where individuals may discover novel interactions with the physical and digital environment. BCIs are expected to become more sophisticated, reliable, and user-friendly, given a sustained effort to advance research and development. While there are still technical and ethical challenges to overcome, the collaborative efforts of researchers, engineers, industry leaders, policymakers, and end-users will lead to responsible and committed efforts to building trustworthy BCI systems. This publication is the first of six POV papers exploring the upside potential, technology, challenges, ethics, and applications of BCI neurotechnology.

Disclosure

Authors are participating in their personal capacity and the views expressed in this publication are those of the authors and do not necessarily represent the views of the funding agencies, the companies, or institutions mentioned.

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