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Non-Invasive Brain Computer Interfaces: Challenges and Opportunities

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1. Introduction

Humans have evolved through their interaction with their environment. Following an evolutionary process, the exploratory capabilities of the human body have progressively extended through the acquisition of ever more refined motor skills. Specifically, the fine control acquired over our upper limbs allows healthy individuals to perform a wide range of complex behaviors. As our environment becomes increasingly digital, novel ways to explore and interact with it are needed. Our ability to seemingly operate a mouse to interact with a computer is a striking everyday-life example of such adaptation. Indeed, our ability to move the mouse precisely and rapidly allows us to interact with graphical user interfaces according to our intentions. However, there are circumstances under which the execution of such visuomotor skills may not be possible.

Using a mouse as an input device may be an inadequate human-computer interaction (HCI) solution for everyone. Indeed, for individuals suffering from upper limb disabilities and severe motor and cognitive impairments, hands-free HCI alternatives are therefore necessary. Additionally, in the context of demanding motor tasks such as driving, performing surgery, and precise tools manipulations, it is desirable to keep the hands on deck while interacting with a computer (e.g., adapting traffic information display, medical imaging visualizations, tuning tool parameters). Furthermore, the complexity and the number of available commands at reach may be limited. These limitations advocate for the development of hands-free HCI that could assist the users in parallel with the complex manual task they are engaged in.

To that end Brain Computer Interface (BCI), a term initially coined by Jacques Vidal (1973), offers hands-free interactions through the online "decoding" of users' brain activity. This type of neurotechnology – also known as Brain Machine Interface (BMI) - originates in the pioneering research of Hans Berger on electrophysiology in the early 1920s. Berger was the first to observe and document rhythmic activity in the brain at a frequency of around 10 Hz, which he called the "alpha wave." Electroencephalography development had a significant impact on the progress of neuroscience. The first creator of the EEG device John Friedrich Tonnes developed the device in 1932 by converting brain activity into recording an electroencephalographic signal using ink pens. However, it was not until the 1960s that the concept of direct communication between the brain and a machine was demonstrated. Edmond Dewan's groundbreaking experiments involved training volunteers in controlling their alpha brain waves. Using an electroencephalogram

(EEG), he could translate the power of these brain oscillations into commands, such as turning a light switch on or off or generating Morse code. Around the same time, Joseph Kamiya pioneered neurofeedback by demonstrating that individuals could regulate their brain activity using visual, auditory, or tactile stimuli to enhance cognitive performance. These early breakthroughs laid the foundation for the development of modern BCI. Today, a brain-computer interface (BCI) is defined as a system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment (Wolpaw & Wolpaw, 2012).

Advancements in neurophysiological sensors, computer science, and embedded computing have sparked renewed interest in BCIs. These neuro-technologies are expanding into various fields, including clinical applications such as assisted technologies and motor rehabilitation, as well as gaming, to enhance players' experiences. Additionally, BCIs are now available to the general public through applications promoting well-being, such as meditation and sleep improvement. These BCIs have become less invasive and offer exciting prospects for human-computer interaction. Indeed, BCI has the potential to alleviate mental and physical loads associated with the repetition of straining actions to improve task performance both in terms of precision and speed, and to promote new forms of interactions to enhance human-machine teaming. Furthermore, BCIs can inform the design of complex systems and dynamically adapt the user interface and task parameters during use.

This chapter aims to showcase the latest technological advancements in the exciting field of research and demonstrate how they have the potential to revolutionize the HCI field. We will mainly focus on non-invasive and mobile BCI as they offer several advantages over invasive BCIs, making them more relevant for HCI and everyday life applications. In addition, we will examine the current challenges and end-user issues related to deploying these technologies in the field. Theories and knowledge in HCI design can play a crucial role in improving the design of BCIs and their usability. We will also discuss how HCI can contribute to optimizing the design of BCIs for a better user experience.

2. The human brain

The human brain is considered one of the most complex organs of the human body (Kawala-Sterniuk et al, 2021; Martinek et al, 2021; Kawala-Sterniuk et al, 2020; Figaji, 2021). Until today it is impossible to recreate and simulate its entire structure and functioning

(Kawala-Sterniuk et al, 2021; Figaji, 2021; Zhang, 2014). The human brain consists of over 100 billion neurons, and each can create up to 10,000 synaptic connections with other nerve cells (Martinek et al., 2021; Weiss, 2000). Despite consisting mostly of water and only accounting for 2% of the whole body mass, the human brain consumes around 20% of energy intake of an adult (Herculano-Houzel, 2011; Herculano-Houzel, 2012). The human brain sends, receives, and coordinates information throughout the body. The brain-body communication is crucial for a functional life; from daily activities such as learning, moving, resting, eating, and sleeping to complex cognitive tasks such as reasoning, strategizing and decision-making, everything is commanded by the human brain. Understanding how the brain communicates with the body and how it drives behavior is fundamental to developing and improving novel human-machine technologies. Therefore, this section of the chapter will introduce the fundamentals of brain neuroanatomy, describing the source of the signals, the physiological basis, and the wearable neuroimaging techniques most suitable to measure brain activity.

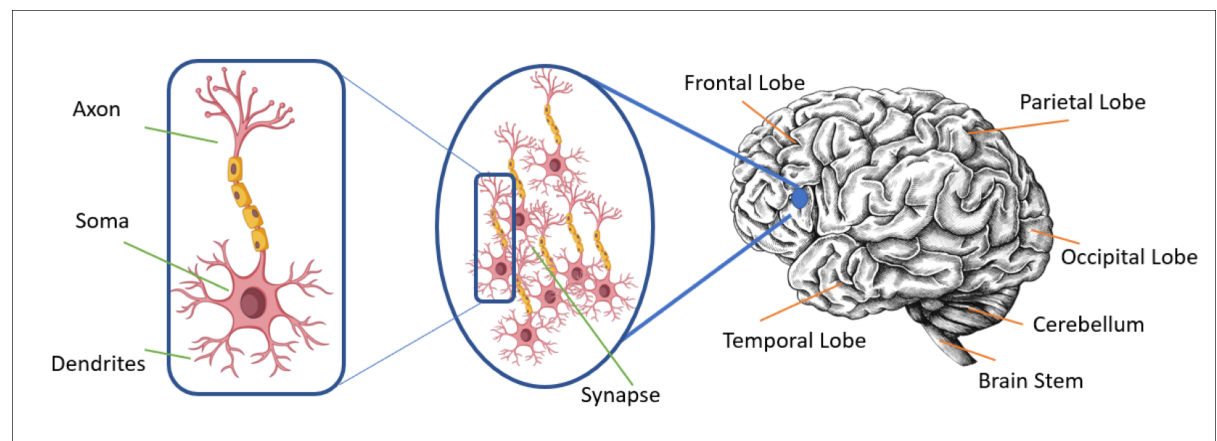


Figure 1. Multi-scale brain organization from neurons (left), synapses and circuits (middle) and representation with major cortical lobes (right) where brain circuits and larger networks are formed with cascaded networks of neurons (middle) and individual pyramidal neurons as a computational unit (left).

2.1 Neuroanatomy of the human brain

A complete description of structural and functional organization of the human nervous system would require several dedicated volumes. In this section, we provide an introduction, particularly starting with the building block cells that are termed neurons, and

the multi-scale structures that emerge from chains of neurons. Information moves from one region of the brain to another via chains of neurons that can transmit signals over long distances and are inter-connected as a highly complex adaptive neural network. When the nerve fibers of region-spanning neurons form distinct bundles, these are called nerve tracts. Example of a major nerve tract is the corpus callosum, the thick bundle of neurons connecting the left and right cerebral hemispheres. The structural health, functional significance of certain areas of the brain, and the connectivity between different regions are topics of intense research for understanding neurological and psychiatric disorders as well as for relating behavior and psychological processes. The human brain, encephalon, is approximately 3 pounds of spongy tissue within a bony enclosure, the skull. Inside the skull, cerebral hemispheres are enveloped with three layers of protective membranes, called meninges. The outermost membrane is known as the dura mater that adheres to the inside of the skull. Between the dura mater and the underlying membrane is cerebrospinal fluid that provides an additional buffer for mechanical protection. There are two cerebral hemispheres, left and right, that are almost identical but have subtle dissimilarities that relate to the different information processing styles. Cerebral hemispheres can be further divided into four lobes: frontal, temporal, parietal, and occipital. The left and right frontal lobes are at the front of the brain, above the eyes and just beneath the forehead. The frontal lobe is primarily responsible for higher executive functions, expressive language, and voluntary movements: initiation, planning, execution, and regulation of complex motor movements and actions. The primary motor region, the precentral gyrus, contains the sites for the initiation of specific movements of various parts of the body. This region is distributed like an upside-down homunculus (miniature man) representing the neurological map for sensory or motor functions for different parts of the body and an ideal target for BCI input signal for motor movement and imagery.

The homunculus is split in half, with motor representations for the left side of the body on the right side of the brain, and vice versa. The amount of cortex devoted to any given body region is not proportional to that body region's surface area or volume, but rather to how richly innervated that region is. Areas of the body with more complex and/or more numerous motor connections are represented as larger in the homunculus, while those with less complex and/or less numerous connections are represented as smaller. The resulting image is that of a distorted human body, with disproportionately huge hands, lips, and face. Structural damage and function deficits in motor systems could result in a number

of clinical problems that neuroprosthetic and BCI research targets. Similarly, stressors such as fatigue or high mental workload can impair healthy people's cognitive ability which BCI could help to mitigate their effect (Dehais et al, 2019a). Interested readers are encouraged to refer to neuroanatomy reference books and clinical textbooks such as Patestas and Gartner (2016) and Crossman and Neary (2018).

2.2 Electrophysiological signals

Neurons are cells responsible for the information flow along the nervous system. A neuron is divided into the soma or cell body, axon, and dendrites (see figure 1). Each part plays a fundamental role in communication between two or more cells. The soma hosts the nucleus and organelles crucial to keep the neurons life. The axon is an extended cable connected to the soma, and it is responsible for transmitting the nerve impulse generated to other neurons and muscles. The dendrites are neurons' branches responsible for receiving signals from other cells (Bear et al., 2001). The neuronal activity involves pumping ions in and out of cell membrane. Neurons are "charged cells" as they concentrate on several ions such as sodium (Na⁺), Potassium (K⁺), and calcium (Ca⁺). The extracellular medium is also "charged" by other ions, mainly Na⁺, Ca⁺, and chloride (Cl⁻). The "neuronal membrane" involves neurons and works as an isolator that balances the extra and intracellular environment. Ions transit from one neuron to another through "gates" in the neuronal membrane, called "channels."

Synapse is the communication process between a neuron and a target cells, such as another neuron, muscle, or gland. It consists of a presynaptic cell sending an electrical impulse to a postsynaptic cell. The synapse is classified as electrical or chemical, according to the signal messenger. In the electrical synapses, the ions flow directly from one cell to another (Figure 1). In the chemical synapses, chemical structures named neurotransmitters carry the signals. It is important to note that the human brain has more than 80 billion neurons, all connected and communicating with each other forming over trillion connections. A connectome is a comprehensive map of neural connections in the brain, and may be considered of as its blueprint "wiring diagram". The emerging field of connectomics offers a powerful analytic framework for understanding neural mechanisms in health and localizing pathology, tracking patterns of disease impact in nervous system (Bassett & Sporns, 2017; Fornito et al., 2015).

2.3 The neurovascular coupling

Neurovascular coupling (NVC) is a mechanism that describes the link between neuronal activity and blood flow in the brain. When a brain region increases neural activity, more action potentials and synaptic activity occurs, increasing the energy demand that requires oxygen (O₂) carried to the brain with blood. More blood is delivered to that specific more active area to compensate for the consumption, and keep the system in balance. The additional blood supply increases the oxygen rich blood (with increased flow and volume) in the active brain region leading to an O₂ increase delivered to the neurons. In this process, the oxygen molecules are carried in blood by the hemoglobin molecule, a protein of the blood red cells. When the hemoglobin is attached to oxygen, it is called oxygenated hemoglobin (HbO); otherwise, it is in reduced form, deoxyhemoglobin (HbR). According to the NVC, after a stimulus, a transitory hemodynamic response can be observed by an increase in the HbO and a decrease in HbR. The hemodynamic response Function (HRF) is a mathematical-computational model used to describe this neurovascular process. Thus, neurovascular coupling and HRF are fundamental concepts for understanding brain hemodynamic responses.

Hemodynamic measures of brain activity provides localized measurement of active and inhibited brain areas that can be used to identify spatiotemporal patterns linked to cognition, emotion, perception, and motor tasks and can be used to evaluate cognitive workload, mental effort, and neural efficiency consistent with Neuroergonomics (Ayaz & Dehais, 2019). Diverse neuroergonomics applications have benefited from features of hemodynamic signals, such as the investigation of the mental workload of trainee pilots and flight simulators (Ayaz et al., 2013; Gateau et al., 2018; Tang et al., 2022). Furthermore, hemodynamic signals have been measured in both resting state and goal-driven cognitive tasks and have been used in several applications to understand clinical and healthy populations. Task-related studies have demonstrated the relationship between features of hemodynamic signals and executive functions such as attention, memory, and inhibitory control (Curtin et al., 2019; Harrivel et al., 2013; Jahani et al., 2017). Thus, like electrophysiological signals, brain hemodynamic responses provide invaluable information about the human brain's mental states.

3. Portable brain imaging technologies for BCI

The rapid development of science and technology brought interest in analyzing biomedical data and their use for control purposes (Kawala-Sterniuk et al, 202; Martinek et al., 2021; Malin et al, 2013; Tyagi et al, 2022). Analysis of brain signals bright the era of Brain-Computer Interfaces, which can be divided into two main groups - invasive and non-invasive systems (Steyrl et al, 2016; Waldert, 2016), as illustrated in Figure 2. Thus, both types of BCIs work in a way where the information is being exchanged between the brain and computer in real-time (Kawala-Sterniuk et al., 2021; Waldert, 2016). Also, brain activity applied for BCI purposes is processed either directly or indirectly (Kawala-Sterniuk et al., 2021, Chenane & Touati, 2018; Nazeer et al, 2020), where direct measurement means e.g. EEG (Kawala-Sterniuk et al, 2021) and indirect - e.g., blood oxygen measurements (Kawala-Sterniuk et al, 2021; Nazeer et al, 2020). BCI systems are not mind-reading devices (Martinek et al., 2021), but rather systems where the motor action is carried out directly without muscle engagement and by using brain activity only (Kawala-Sterniuk et al., 2021).

In this chapter, we mainly focus on non-invasive BCIs that do not require surgical intervention, and which become the subject of interest of researchers around the world (Grübler et al, 2014; Kawala-Sterniuk et al, 2021; Douibi et al, 2021; Remya & Sumithra, 2023). The aforementioned BCI's non-invasiveness contributes to their commonness and potentially short-term transition from the laboratory to the real-world environment (Nagel & Spüler, 2019; Douibi et al., 2021; Friedman et la, 2017; Benaroch et al, 2022). Brain imaging techniques such as magnetoencephalography (MEG) (Philip et al, 2022; Xu et al., 2022), positron emission tomography (PET) scan (Alharbi, 2023), and functional magnetic resonance imaging (fMRI) (Singh et al, 2023) can also be applied for non-invasive BCI systems (Min et al, 2010). However, due to their cost and size, these methods are not popular and applicable to portable (out of the lab) brain-computer interfaces (Sosa et al., 2011, Paulmurugan et al, 2021). There is an abundance of EEG measurement equipment on the market. However, the devices that are designed to push BCI systems out of the laboratory environment are inexpensive, off-the-shelf devices, including the OpenBCI headsets (see: Fig. 3). The next section details two mobile technologies for BCI, namely electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS).

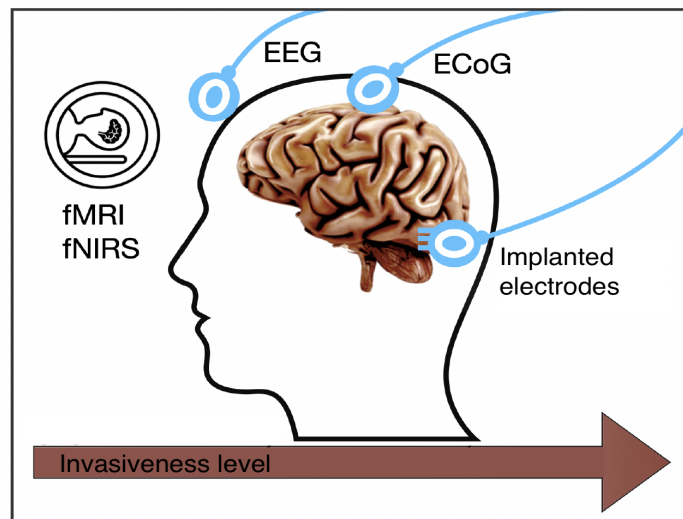


Fig. 2. BCI systems: invasiveness level.



Fig. 3. A representative low cost EEG headset from OpenBCI, New York.

3.1. Electroencephalography (EEG)

EEG is the most popular technique in the non-invasive BCI community due to its high temporal resolution (Jeong et al., 2022; Kawala-Sterniuk et al., 2021; Martinek et al., 2021; Pastor & Vega-Zelaya, 2023; Kübler, 2020). Surface electrodes placed along the scalp measure the voltage fluctuations of large populations of aligned pyramidal cortical neurons because the electric field of a single neuron is too weak to be detected through the skull and tissue layers at the surface level (Cohen et al., 2014). However, this technique does not provide access to actual brain sources, as each electrode captures a mixture of the different neural activities. This is similar to recording and trying to identify individual conversations during a crowded party using several microphones placed in the ceiling. Each microphone would capture a combination of different "vocal sources" making it difficult to isolate individual voices. Instead, the microphones would mostly detect simultaneous shouts and laughter during episodes of crowd behavior.

Another limitation of EEG is that its signal is strongly affected by several artifacts like eye movements (including eye blinks), muscular activity (e.g., jaw clenching, body motions), and displacement of electrodes (Cohen et al., 2014). A common artifact in the EEG signals is the peak in the 60/50 Hz frequency because of the electrical network feeding the power for device operation. Typically notch filters are applied to remove such artifacts, and bandpass filters eliminate high-frequency noise and low-frequency drifts. It is important to pre-process the signals before using them for BCI or any other application. Furthermore, the EEG is optimum for capturing fast brain responses since it has a high temporal resolution with devices achieving sampling rates of 1000 HZ; however, if the research question is about where in the brain, EEG is not optimum since its spatial resolution low when compared to other neuroimaging modalities. Most EEG-based BCI studies have used research-grade systems with wet electrodes that require conductive gel on the scalp for higher signal-to-noise. While these devices offer higher classification accuracy, they have a long setup time and are impractical for everyday use. Recent technological advancements have led to the development of dry-electrode EEG systems with wireless communication protocols (Di Flumeri et al., 2019). These systems allow for streaming electrophysiological data online and give users greater freedom of movement. These advancements open up promising possibilities for pushing BCI outside the lab and into real-world scenarios like healthcare, aviation, entertainment, and domotic.

Usually, the EEG is collected while a subject is under a specific condition, for instance, sleeping, resting, or performing cognitive tasks. Mathematical and computational methods are applied to the EEG signals of each electrode to understand the brain waves related to each mental state. A traditional approach is power analysis. In this methodology, the frequency bands present in the signals are explored by applying a Fourier Transform (F-T), and the amplitude of the component is computed. The most common brain waves are the delta (<4Hz), theta (4-8Hz), alpha (8-12 Hz), and beta(13-30Hz). For instance, an increase of alpha amplitude is found in the occipital region (the brain region associated with vision) when comparing eyes closed and eyes opened states (Hohaia et al., 2022); the delta wave is associated to sleeping process in humans and non-humans animals (Amzica & Steriade, 1998); alpha and beta waves were found in studies about several executive functions such as attention, memory, inhibitory control, and decision making (Klimesch, 1999).

Another conventional methodology applied to the EEG signals to extract information about mental states is the event-related potential (ERP) analysis. As the name implies, ERPs are brain responses to a specific event; the event may be a sensorial, motor, or cognitive stimulus. Instead of decomposing the EEG time series in different frequencies, the ERP analysis works in the time domain by looking at the amplitude of the EEG signals some milliseconds after the stimulus onset. The P300 is a component of an ERP, also known as an evoked potential; it is elicited when an unexpected stimulus (oddball) occurs within more frequent expected stimuli. The letters used in the ERP names represent the amplitude polarity (positive =P, or negative = N), and the numbers represent the time the amplitude was deflected after the stimulus onset; for instance, P300 means a Positive deflection in the amplitude of the EEG signal after 300ms after the stimulus happened. The odd-ball and steady-state visually evoked potentials (SSVEP) are experimental protocols used to elicit P300 potentials and have been used with a brain-computer application. In the oddball paradigm, the participants are asked to focus on a target which can be a letter, a screen, or a sound, depending on the region of the brain investigated, while non-target items are more frequent. When the target appears, a slight positive deflection in the EEG amplitude occurs. The process is repeated several times so that the average of the EEG signals will show the P300 after approximately 300s of the target occurrence.

3.2 Functional near infrared spectroscopy (fNIRS)

Functional near-infrared spectroscopy (fNIRS) is a neuroimaging modality that measures brain hemodynamic signals by emitting and detecting near-infrared light over the scalp (Ayaz et al., 2022). There are three general types of fNIRS devices, the continuous wave (CW), the time (TD), and the frequency domain (FD). The continuous wave is the most commonly used type, and fNIRS measures changes in the HbO and HbR concentrations in the measured brain areas. In these systems, the emitted light travels across the hair, tissues, skull, and scalp; the obstacles scatter part of this light, and other parts are transmitted into the brain and absorbed by chromophore molecules. After the emitter-brain trajectory, some light is scattered and detected by detectors placed in the scalp. The concentrations of HbO and Hb are computed by applying the modified Beer-Lambert law to the light intensities. According to the neurovascular coupling and hemodynamic response function, brain activation is intrinsically related to increased HbO and decreased Hb after stimulus onset. Thus, the fNIRS CW measurement's principles rely

on the fact that HbO and Hb concentrations provide enough information to infer neural activity in the brain area of interest.

fNIRS devices are composed of a near-infrared light source and light sensors, also called optodes which may be an emitter or detector if it sends or receives light, respectively. Like EEG, fNIRS devices vary in size (portable x lab-based), number, and optode types. The device choice depends on the research question and population. Portable and wearable devices are more suitable for naturalistic experiments with ecological validity that emulates everyday life. However, these systems usually offer fewer sensors than traditional lab-based systems, limiting the scalp coverage region.

On the other hand, for more conventional and well-controlled experiments which investigate different brain areas, the lab-based versions are optimum. They have a better signal-to-noise ratio and measure many optodes to assess localized information from the entire outer cortex. In both cases, portable and lab-based fNIRS have the advantage of being tolerant to motion artifacts and a fast set-up. The fNIRS is a powerful tool for assessing brain hemodynamic responses in several real-world applications. In the BCI field, fNIRS is an emerging and promising tool (Naseer & Hong, 2015). Although most applications are still proof-of-concepts studies or assessments of different algorithms applications to extract features of the fNIRS signals, promising results with satisfactory accuracy have been found (Aranyi et al., 2016; Kaiser et al., 2014; Nazeer et al., 2020). Furthermore, the possibility of measuring two or more brains simultaneously, an approach named hyperScanning, has brought new insights into understanding the neural mechanisms underpinning human interaction (Liu, Y., et al 2017; Liu, T., et al., 2021; Miller et al., 2019; Tang et al., 2020). Other applications, including but not limited to education, sports, and real problem solving, have also taken advantage of fNIRS hyper-scanning paradigms (Barreto et al., 2021; Li et al., 2020; Mayselless et al., 2019). Even though fNIRS is a potential tool to assess the human brain, it has limits to be considered. Due to technical limitations, the available systems can only measure outer cortical regions (the brain's outer layer) that is close to the surface. Therefore, fNIRS is unsuitable for investigating hemodynamic responses from deeper cortical regions. Additionally, the hemodynamic signals are slow responses, only appearing some seconds after the stimulus onset. It makes fNIRS more appropriate to studies interested more in "*where*" than "*when*" in the brain the activation happens. Figure 4 illustrates a Cortivision (Lublin, Poland) inexpensive fNIRS headset. The device is portable and easy to use. In order to obtain good-quality of signals, it

is necessary to cover the headset with the electrodes mounted. Figure 5 also presents the fNIRS (Cortivision, Lublin, Poland) headset (right) and the electrodes montage (left), where the channels are placed following the international '10-20' system.



Fig. 4. A representative fNIRS headset from Cortivision (left and middle) with appropriate cover for proper recordings (right).

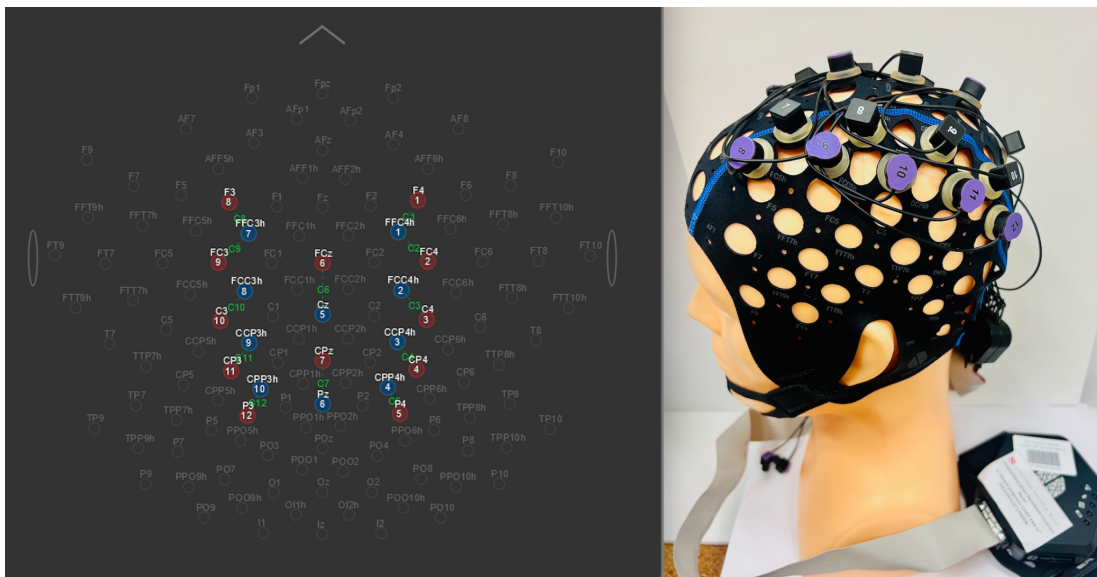


Fig. 5. Cortivision fNIRS headset (right) and sample channel location (left). The channels in the fNIRS technology consist of sources and detectors

4. Typology of brain-computer interfaces

In the previous section, we discussed brain imaging technologies that can support communication in a computerized environment without requiring physical movement. There are three main categories of BCIs: active, reactive, and passive (for reviews, see Nam, Nijholt & Lotte, 2018, Clerc. Bougrain & Lotte, 2016a and 2016b). Active and reactive BCIs are designed to translate cerebral activity into commands that can be used to control external devices. Passive BCIs, on the other hand, facilitate implicit interaction by adapting the human-machine teaming based on the user's mental state. These different brain imaging techniques and types of BCI can be integrated into hybrid systems, resulting in more robust and versatile technologies with improved usability (see for a review Tresols, Chanel, & Dehais, 2022).

4.1 Active BCI

Active BCI (aBCIs) allows users to "actively" control an artifact (e.g., prosthesis, mouse cursor) by generating a prototypal mental activity that is interpreted by an algorithm (Figure 6). Currently, no-invasive aBCIs cannot interpret a person's thoughts or intentions. The users are typically required to train themselves to produce distinct brain signals deliberately. The most popular aBCI paradigm involves mental imagery in which the user is required to imagine the movement of a limb without physically executing it. In order to be distinguished through the use of EEG (Kevric & Subasi, 2017) or fNIRS (Zhang et al., 2017), these "mental" movements must generate unique neural patterns such as left vs right-hand movement. These later aBCI offers two degrees of freedom, such as the ability to control an object up or down (Andreev et al., 2016). Some authors managed to increase the number of available commands up to four by combining feet and hand mental imagery to control a car (left turn, right turn, acceleration, deceleration) (Zhao, Zhang & Cichocki, 2009). From an implementation point of view, aBCI involves a calibration phase in which the machine learning algorithm learns to recognize these particular commands by analyzing examples of brain signals provided by the BCI user. After completing this human-machine co-learning process, the person can mentally interact with a system, such as an airplane or robot, to guide it. However, existing BCI systems are not flawless and often misconstrue the understood mental commands, which limits their use in critical control applications.

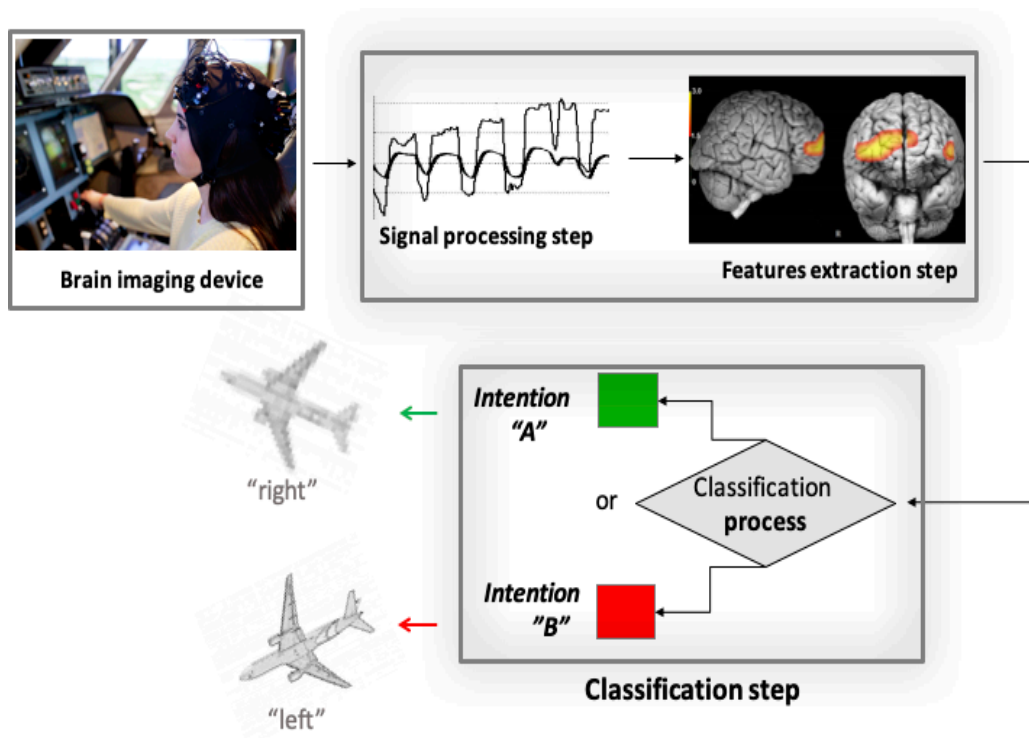


Figure 6: illustration of an active BCI (aBCI) or a reactive BCI (rBCI) implementation. The process of designing such BCI involves several stages, including acquiring signals (such as EEG, fNIRS), preprocessing to eliminate artifacts and enhance signal quality, extracting features) and using machine learning for classification and translation of the brain signal into command (here controlling a plane).

4.2 Reactive BCI

In contrast to active BCI, where the users are required to deliberately produce brain signals to interact with the BCI, reactive BCI (rBCI) discriminates the user's cerebral responses elicited by the different presentation of stimuli and translates them into associated commands. For example, when visual targets are presented, they can elicit a specific brain response called a visual evoked potential (VEP). One well-known component of the VEP is the P300, a positive deflection that occurs approximately 300 milliseconds post-target presentation. The P300 speller is one of the most famous BCI that takes advantage of these neural responses (Farewell & Donchin, 1988). It involves displaying a matrix on the screen containing characters (letters and digits to be typed). The user is instructed to focus on a particular symbol, and then the rows and columns of the matrix are flashed randomly. When the row or column contains the chosen character, a P300 is generated that is decoded by a trained classifier that then types the corresponding character (see Figure 2). The classification problem complexity initially involving 26+ classes (depending on the script used) at all stages of the selection process has been simplified

through predictive entry selection and automatic filling approaches based on dictionaries and grammatical rules (Ryan et al., 2011).

Moreover, the P300 ERP BCI paradigm is inherently limited by its discreet temporal nature. Indeed, overlapping ERPs are difficult to disentangle in the continuous data, especially online, where the range of signal processing methods that can be applied is limited. Therefore, ERP such as the P300 needs to be spaced temporally and repeated over several trials to ensure a sufficient signal-to-noise ratio and be effectively extracted.

Another type of rBCI takes advantage of Steady-States VEP (SSVEP) neural responses (Zhang et al., 2014, for a review, see Li, He, Li, & Qi, 2021). SSVEP refers to the rhythmic entrainment of neural populations of the visual cortex to repetitive and periodic visual stimulation (Joon Kim et al., 2007) - see Figure 2. Flashing a checkerboard (or a LED) at a fixed frequency (e.g., 15Hz) will induce 15 Hz oscillations over the visual cortex that can be extracted in the EEG signal. In a typical SSVEP-based rBCI, several stimuli are presented simultaneously at different frequencies (e.g., the letter “A” flashed at 15Hz, letter “B” flashed at 10Hz, etc...). By focusing one’s attention on a specific stimulus (e.g., the letter “A”), a SSVEP response is elicited at the corresponding frequency (15Hz). The decoded response triggers an associated output command, such as a key press for a text-entry rBCI (i.e., the letter “A” will be typed). SSVEP-based rBCIs offer high classification performance and many commands (Nakanishi et al., 2018), with relatively short training time requirements compared to mental imagery-based BCIs. However, rBCI systems, unlike aBCI, are generally not self-paced, meaning that the computer regulates the pace of interaction and not the user. An emerging paradigm for rBCI is to replace the periodic flickers with a-periodic, binary (zeroes and ones corresponding to black and white states), random code sequences. This so-called code-VEP (Martínez-Cagigal, 2021) evokes a series of discrete Visually Evoked Potentials (VEP). The code generated is split into phase-shifted sequences that have minimal cross-correlation and that are assigned to different targets (Thielen et al., 2017). By learning the relationship between short sliding windows of EEG signals and the elementary bits (0 and 1) of the cVEP stimulus, the decoding method produces a sequence that can be matched online to the patterns assigned to the different targets (Nagel and Spüler; 2019). This new paradigm has several advantages, most notably in terms of calibration time, classification performance, and user experience. It is important to note that although all the aforementioned rBCI paradigms (P300, cVEP, SSVEP) were based on visual stimulation (which is the dominant approach),

other modalities such as the auditory or somatosensory have nonetheless been developed and may be relevant for specific applications (Chabuda et al., 2019).

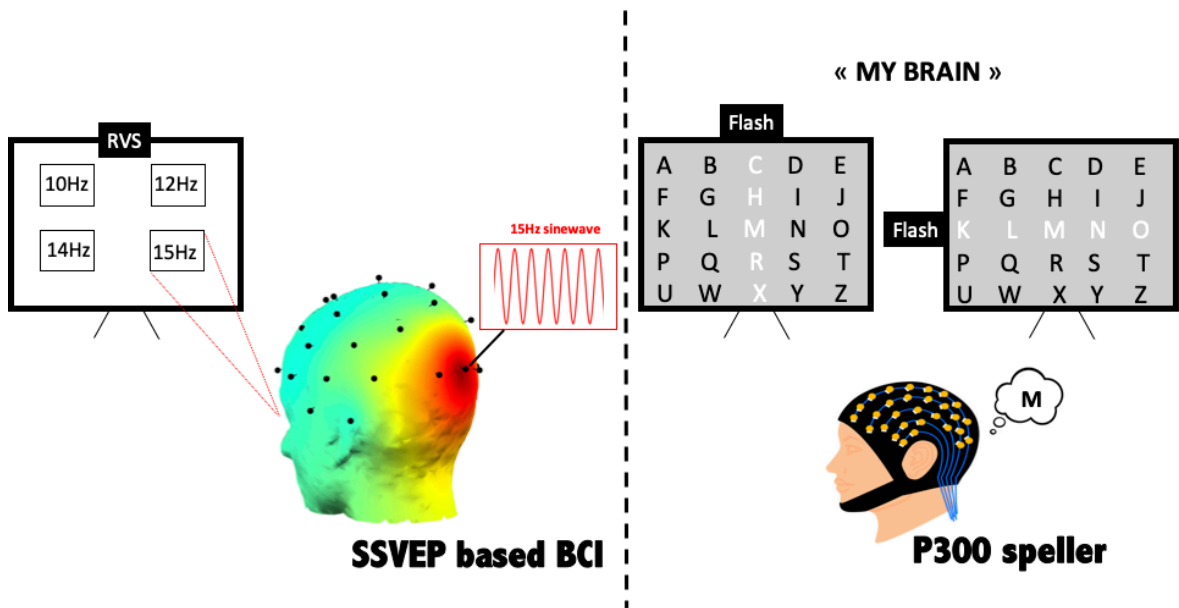


Figure 7: illustration of two types of a reactive BCI (rBCI) implementation. Left: several rapid visual stimuli (RVI) are flashed at different frequencies. When the user is focusing on one the flicker (eg. 15Hz), his/her brainwaves measured over the occipital cortex oscillate at the corresponding frequency (15Hz). These prototypic brain responses can be decoded by machine learning algorithms and transformed into a command. Right: the P300 speller. The user is instructed to focus on a letter of interest (here “M” so as to start typing the words “My brain”). When the row and column that both contain the chosen letter are successively flashed, a prototypic brain response (P300) is elicited that is then decoded, leading to type the desired letter.

4.3 Passive BCI

Passive BCIs (Zander & Kothe, 2011) are designed to enhance human-machine symbiosis by using (1) machine learning techniques to infer user's mental states (e.g., stress, fatigue, or mental load) and (2) decisions based AI algorithms to adapt the interaction dynamically to maintain optimal engagement (see figure 3). This can be achieved by the dynamic adaptation of the user interface (e.g., modifying an alarm's modality to make it more salient), changing the task and the level of automation between the human and systems, or "adapting" the operator through different stimulation techniques (Dehais, Lafont, Roy, and Fairclough, 2020). The successful implementation of such systems hinges on the ability to assist promptly and appropriately (Parasuraman, Mouloua, & Hilburn, 1999). Failing to trigger the assistance system or triggering it unnecessarily could have adverse effects on human operators (Parasuraman, Hancock, & Olofinboba,

1997). To address this concern, it is necessary to focus on mental states that are reliable predictors of human performance and can be accurately identified through behavioral and neurophysiological measures (Dehais, Lafont, Roy, and Fairclough, 2020, Frey et al, 2014). Moreover, continuous monitoring of brain activity can be utilized in training and skill acquisition to observe the level of the trainee (for example, see Ayaz et al. 2012) and customize/personalize the training (for neuroadaptive training, see Mark et al. 2022). Recent demonstrations of such passive BCIs have been made outside the lab to infer the state of human operators (for a review, see Arico et al., 2018)

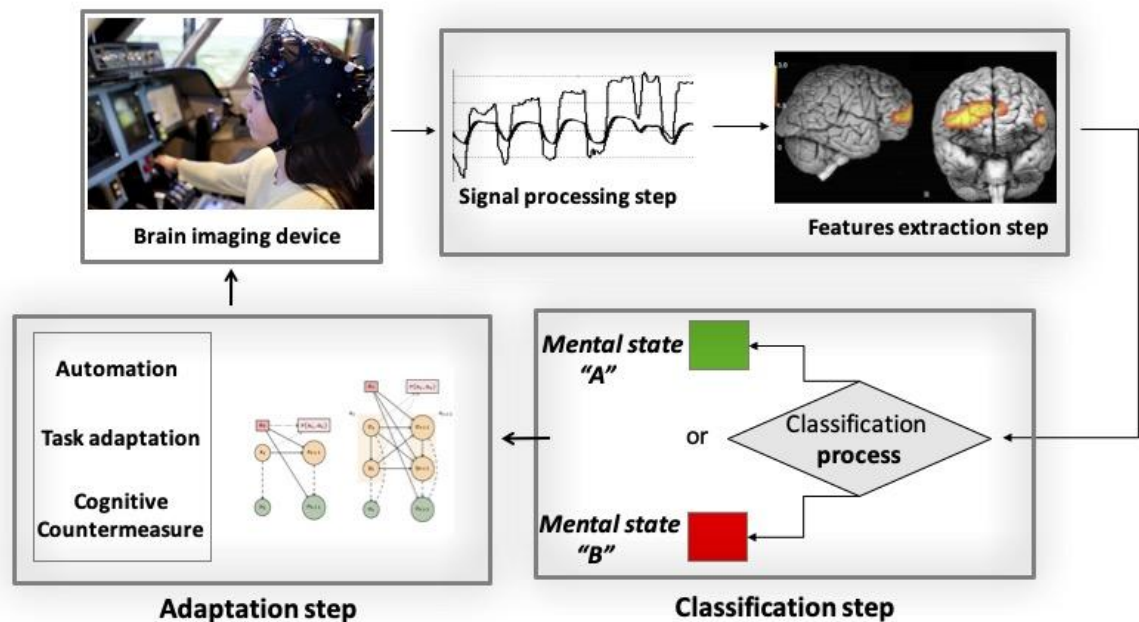


Figure 8. Illustration of a passive BCI (pBCI) implementation. The process of designing such BCI involves several stages, including acquiring signals (such as EEG, fNIRS), preprocessing to eliminate artifacts and enhance signal quality, extracting features) and using machine learning for mental state classification. The adaptation step involves providing the estimated mental state to the system's decision-making unit, which closes the feedback loop.

4.4 Hybrid BCI

The term 'hybrid BCI' (hBCI), which refers to the integration of two or more distinct BCI systems, was introduced by Pfurtscheller et al. (2010). The primary goal of hBCI is to enhance the quantitative performance of BCI systems, including classification accuracy (Yin et al., 2015, Jalilpour, Sardouie, & Mijani, 2020) and increase the number of available commands (Allison et al., 2012; Long et al., 2011; Chang et al., 2016). One first approach is to combine two different brain imaging techniques, such as EEG and fNIRS, to take advantage of the high temporal resolution of the former and superior spatial accuracy

of the latter. Several BCI studies have revealed that their hybridization provides better accuracy than when used separately (see for a review Ahn & Jun, 2017) and higher robustness (Dehais et al., 2018).

A second approach is to mesh different types of BCIs. For instance, Allison et al. (2012) designed a system that combines both motor imagery as an active BCI and SSVEP as a reactive BCI to control a mouse cursor's vertical and horizontal axis, respectively. Similarly, Long, Li, Tianyou, and Gu (2011) implemented an hBCI using P300 to switch and select the desired item and then mental imagery to confirm its selection as a mouse click would do. Alternatively, the hBCI framework has been implemented to inform an active or reactive BCI with a pBCI. For instance, impaired cognitive states, such as fatigue or mental workload, are known to negatively impact the accuracy of reactive and active BCIs (Roy et al., 2015). In this regard, Cotrina et al. (2014) designed a pBCI to estimate the participant's mental workload and then adjusted the recognition characteristics of SSVEP-BCIs accordingly. In a different approach, Dehais et al. (2022) implemented a dual reactive-passive BCI to support bi-directional and enhanced interaction between a pilot and the flight deck (see Figure 4). The rBCI allows the pilots to perform hands-free checklists, while the passive BCI triggers adaptive automation in case of a low level of attention.

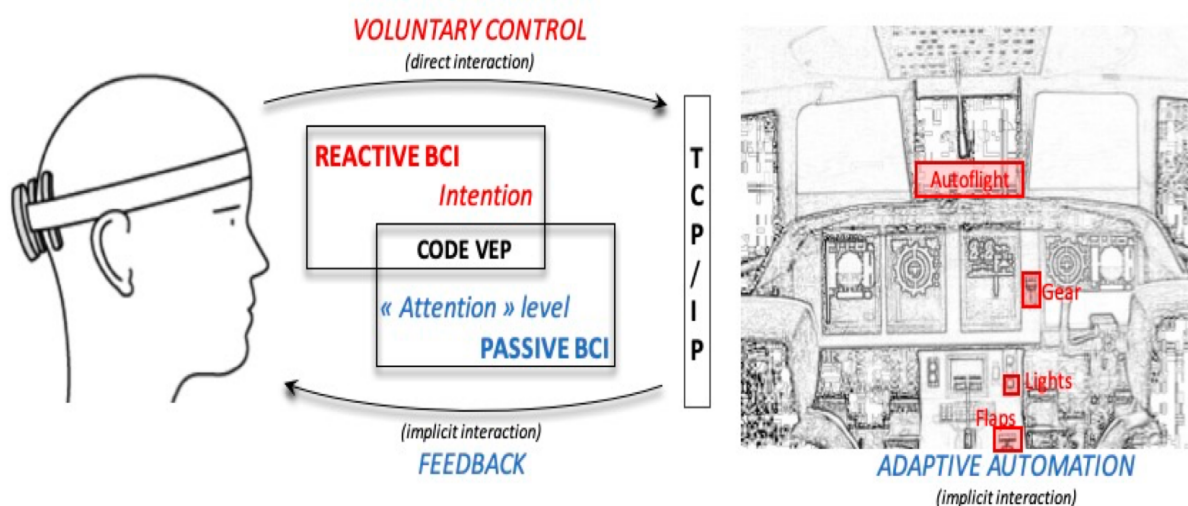


Figure 9. Example of hybrid BCI (hBCI) that combines a passive and reactive BCI that enables human-machine bi-directional communication: (1) the pilots can directly interact with some flight deck actuators with their "brain waves" (e.g., the landing gears - as shown in red), and (2) the flight deck can send visual feedback to the pilot and adapt the interaction when poor cognitive performance is detected. Adapted from Dehais et al, 2022.

4.5. Examples of BCI applications

Brain-Computer Interfaces have a very wide range of applications (Zabcikova et al., 2022), from the control of external devices through the selection of input commands (Kawala-Sterniuk et al., 2021; Trocellier et al., 2022; Benaroch et al., 2022) to assistive technologies to support individuals in the acquisition of skills and the prolonged performance of fatigue-inducing tasks through neurofeedback and adaptive environments. For instance, aBCI and rBCI promote hands-free interaction for a wide range of applications such as operating airplanes, (Fricke et al., 2014;; Rodriguez-Bermudez et al., 2019, Dehais et al, 2022), drones (Nourmohammadi et al., 2018), car (Yu, et al 2016), exoskeleton (Kwak et al, 2015), robotic arm (Peng et al, 2022), construction robot (Liu, Habibnezhad & Jebell, 2021) or playing computer games (Louis et al, 2022, Bonnet et al, 2013). Furthermore, passive BCIs can be used to evaluate and improve the user interface of complex human-machine systems by assessing the mental effort of human operators engaging with various aspects of such systems. The usability of complex systems, including tools, computers, or machines such as wheelchairs (Joshi et al., 2020), mobile displays (McKendrick et al., 2016), aircraft cockpits (Harrison et al., 2014), coffee machines (Sargent et al., 2020) and surgical robots (Shewokis et al., 2017) have been investigated with this neuroergonomic approach.

In the context of virtual and augmented reality (AR/VR), BCIs can be used to detect the user's intention to interact with their virtual environment. For example, if a user wants to pick up an object in the environment, they could simply imagine reaching out to grab it. The BCI would detect this intention and trigger the appropriate AR/VR system action. This would allow users to interact with their AR/VR environment without the need for hand-held controllers or hand gestures (Arpaia et al., 2022, see for review Monteiro et al., 2021). As discussed in section 3.3, BCI can be used to monitor human operators' cognitively degraded state, such as fatigue in critical applications (see for a review Dehais et al., 2020). These measures can trigger the dynamic adaptation of human-machine teaming for more efficient and safer operations. Some demonstrations of such passive BCI have shown that automation can successfully take over during episodes of high workload (Dehais et al, 2022, Aricò et al, 2016) or over-engagement (Prinzel et al., 2000). Additionally, passive BCIs can objectively evaluate interfaces and user experience. By providing real-time indications, they can quantify mental effort, cognitive fatigue, or emotional dimensions related to using an object or a graphical user interface (Wobrock et al., 2015). In addition,

they are also used in neuromarketing (Al-Nafjan, 2022; Mashrur et al, 2022, Brouwer et al, 2021, Kalganis et al, 2021) , or entertainment (Pal et al, 2022; Värbu et al., 2022) .

BCI can be applied to education and human operator training in which sessions are tailored to the trainee at the neurophysiological level (Goble et al, 2023, Mark et al, 2022, Stephens et al, 2018). Similarly, BCI supports neurofeedback applications in which participants receive real-time feedback about their brain activity in response to specific cognitive tasks, allowing them to learn to modulate their own brain function (for a review, see Geppert et al., 2017). It is possible to identify factors that contribute to impaired executive functioning and to develop interventions that help people to manage these factors better. This type of BCI application has the potential to improve executive functioning and overall well-being in a variety of settings, from clinical applications (Geppert et al., 2020), sports (Christie et al., 2020) to the workplace (Massar et al., 2015) and educational settings (Eroğlu et al, 2022) and beyond.

BCI can also be used to rehabilitate people suffering from various types of movement disorders (Colucci et al., 2022; Alashram et al., 2022; Chen, Yu et al., 2022). Sometimes the neurorehabilitation process can be combined with entertainment, like in (Jadavji et al, 2022), where BCI is beginning to be applied as a computer game for rehabilitating children with severe neurological disabilities. They can be used to assist individuals with motor disabilities in engaging with different external devices, such as "neuro-chat technology," to enable communication among individuals or to operate orthosis and prosthesis (see for review Hramov et al., 2022). Work is also underway on the brain-to-brain interface, which is supposed to enable communication between two users without the participation of a computer (Ali et al., 2022). Eventually, these neurotechnologies could be used for diagnosing and online monitoring patients suffering from epileptic seizures (Maksimenko et al., 2017). Studies, such as clinical depression scores and predictions of brain age, have been performed by applying machine learning algorithms to resting-state hemodynamic signals (Yoshida et al., 2017).

There are several promising avenues to extend the range of non-invasive BCI applications. By capitalizing on wearable brain and body imaging technologies (Ladouce, 2017; Stangl et al., 2023, Gramann et al, 2021) and state-of-the-art human activity recognition approaches (Qin et al., 2020), BCI could be taken outside of controlled environments (laboratory and clinical settings) and paradigms that dictate the pace of the interactions and involve the performance of additional artificial behaviors (e.g., attending

to a monitor screen). Indeed, based on the contextual information provided by wearable devices, the BCI interaction can be adapted to better fit the needs of the individual at any given moment. For example, the detection of home appliances through the combination of scene camera and computer vision or by proximal device scanning (through bluetooth communication) may prompt the presentation of the interface. The combination of brain and body sensors would provide useful information to detect and predict the occurrence of risky behaviors (e.g., locomotion in Parkinson's disease patients see Mustile et al., 2021) and trigger assistive approaches preemptively.

Moreover, wearable Augmented Reality systems may provide a solution to superpose a BCI panel (elaborating on the concept presented on the bottom panel of Figure 5) to objects that have been recognized as "of interest" or providing "affordances" to the user to enable brain-to-device interactions. Future generations of non-invasive BCI will leverage the potential of brain and body wearable sensing devices by fusing multimodal information to better adapt the operation of BCI (i.e., on and off states) in a timely manner that can be extended to a broader range of applications.

5. BCI and end-user related issues

While BCIs offer interesting prospects to improve human-machine symbiosis, these technologies still face several end-users-related issues presented in the following sections.

5.1 Calibration

One strong limitation of BCIs (active, reactive, and passive) is related to the calibration phase. In the case of pBCI, the calibration requires the induction of degraded mental states such as stress, fatigue or mental overload in a repetitive fashion to train the classification algorithms. This is highly challenging to accomplish in laboratory settings or in real-life scenarios as it is difficult to induce such cognitive states. In the case of active and reactive BCIs, the user has to generate specific and distinct mental commands so as to calibrate the learning algorithm. The performance of the BCI system highly depends on the subject's engagement during the calibration, which is long and tedious (Li, & Zhang, 2012). The higher the number of classes (or "commands") to be learned by the calibration algorithm, the longer this training is.

A typical example is the Chen et al. (2022) 's study which demonstrated the successful implementation of a rBCI for controlling a 120-key keyboard, offering a vast

range of commands. However, the system requires a 40-minute calibration process that must be repeated before each use, which limits its practicality. In this latter case, the authors used SSVEP-based BCI and template-based approaches requiring several examples of EEG responses for every class. Shifting this paradigm to code-VEP could alleviate this issue (see section 3.2). Indeed, the bitwise decoding of code-VEP is trained on a limited number of trials, and this model can then be applied to any other sequence. A major advantage of this approach is. Therefore, the reduction in calibration time as model training is independent of the number of classes (Thielen et al., 2021). For instance, Darmet et al. (2022) showed that such an approach could reduce calibration time to 2 minutes in a PIN code typing task.

One must remember that this calibration phase has to be done for each new use since physiological signals vary across days and are affected by fatigue (Hinss et al., 2023). Researchers have turned to transfer learning methods that allow data from previous calibration sessions of the same subject (or other subjects) to train machine learning algorithms and reduce calibration time (Wan et al., 2021; Darmet et al, 2023). With this approach, open data is needed, which is an attractive option for tackling this issue. The underlying idea is to gather and share on-line large standardized datasets of physiological data collected under different settings. The open dataset provides the scientific community with a cost-effective way to validate algorithms and compare their performance. More importantly, it will allow the design of BCI machine learning algorithms that are optimally invariant to strong variabilities between users and within-users (Hins et al, 2023). BCI designers with a computer-science background often overlook the potential for improving the relationship between the user and BCI beyond the formal work. Controlling a BCI is a skill that requires learning, similar to driving a car. However, at present, researchers have yet to determine an effective and useful approach to facilitate the learning process. For instance, studies by Allison et al. (2010) and Jeunet et al. (2016) have highlighted the significance of individual factors in mastering a BCI. Indeed, the user receives limited information about their performance during the calibration and training phases, especially when their performance is poor. The feedback provided is often unimodal and low-informative, typically visual. The current approach to training tasks is often repetitive and not personalized to the user. To address this issue, this work proposes developing a user model that can predict the user's performance based on their personality,

skills, and other relevant factors, which can then be used to tailor the design of the BCI and training program.

5.2. Attentional issues

A critical aspect to consider for the design of BCI is its degree of intrusiveness. Ideally, the interface implementation should seamlessly support a targeted function without interfering with other behaviors. This is particularly problematic when considering aBCI as users cannot focus on another task while performing mental imagery. This means that pilots controlling a plane with their minds cannot perform secondary tasks such as responding to radio communications or dealing with critical failures. Indeed, some studies demonstrated that the BCI reliability could be affected when the participants face high mental demands and multitasking scenarios (Dehais et al 2022, Vecchiato et al. 2016). Moreover, operating these aBCI is extremely effortful and induces mental fatigue (Wolpaw et al., 2015), which in turn compromises the BCI efficiency (Myrden & Chaw, 2015).

Attentional issues can also be found during the operation of rBCI. For instance, SSVEP based BCI uses repetitive visual stimuli that may capture cognitive resources away from the very task/behavior that is supposed to be assisted/supported by the BCI. Under high luminance intensity LED arrays alternating between on and off states or through pattern reversal stimuli presented on computer displays alternating between darkest black to brightest white, stimuli used in rBCI have been particularly salient and distracting. Dominant theories of attention (Wickens et al., 1983) posit that attentional processing is directly limited by the pool of cognitive resources available at a given time. The allocation of resources has been modeled as being driven by two types of influences: bottom-up and top-down (Desimone & Duncan, 1995). The top-down influence refers to the exploration, filtering, and processing of information that are relevant to higher-order cognitive strategies.

As opposed to the goal-directed strategy, bottom-up influences relate to the exogenous attraction of attentional resources toward processing information whose features and properties are particularly salient (Peters et al., 2005). Consequently, objects that stand out from the background, such as SSVEP (high contrast, brightness, motion, color intensity) may initially grasp attention at the expense of other objects that are more relevant to the task undertaken (Theeuwes, 2010). The competition for cognitive resources

introduced by the presence of visual stimuli embedded in the interface is only one of many other issues that need to be addressed for P300 and SSVEP-based rBCI.

Another aspect that has been largely overlooked in the design of current BCI is how the interface integrates within the environment. Indeed, most reactive BCIs have been implemented through external graphical interfaces as presented on the top panels of Figure 10. As discussed in previous sections, introducing additional visual information in the environment may be distracting and detrimental to users' performance. Moreover, engaging and interacting through the interface necessarily implies looking at it. While looking at the interface to input commands, the user cannot fully attend to the actual behavior/task undertaken.

Furthermore, to verify the accuracy of the command selected by the BCI, the user needs to go back and forth between the interface and the working area/action field. This feedback is crucial, especially in the early stages of interactions with a BCI system. The user gets a grasp of the system's idiosyncrasies and progressively learns to operate more effectively. These repeated saccades may induce fatigue over time which makes for a poor and frustrating user experience. An elegant solution to this issue is illustrated in the bottom panels of Figure 10. The interaction becomes more continuous through the superposition of the BCI graphical interface to the area of action/environment through AR lenses. With such embedded interfaces, the users can maintain their foveal focus on the task/behavior undertaken and monitor it attentively.

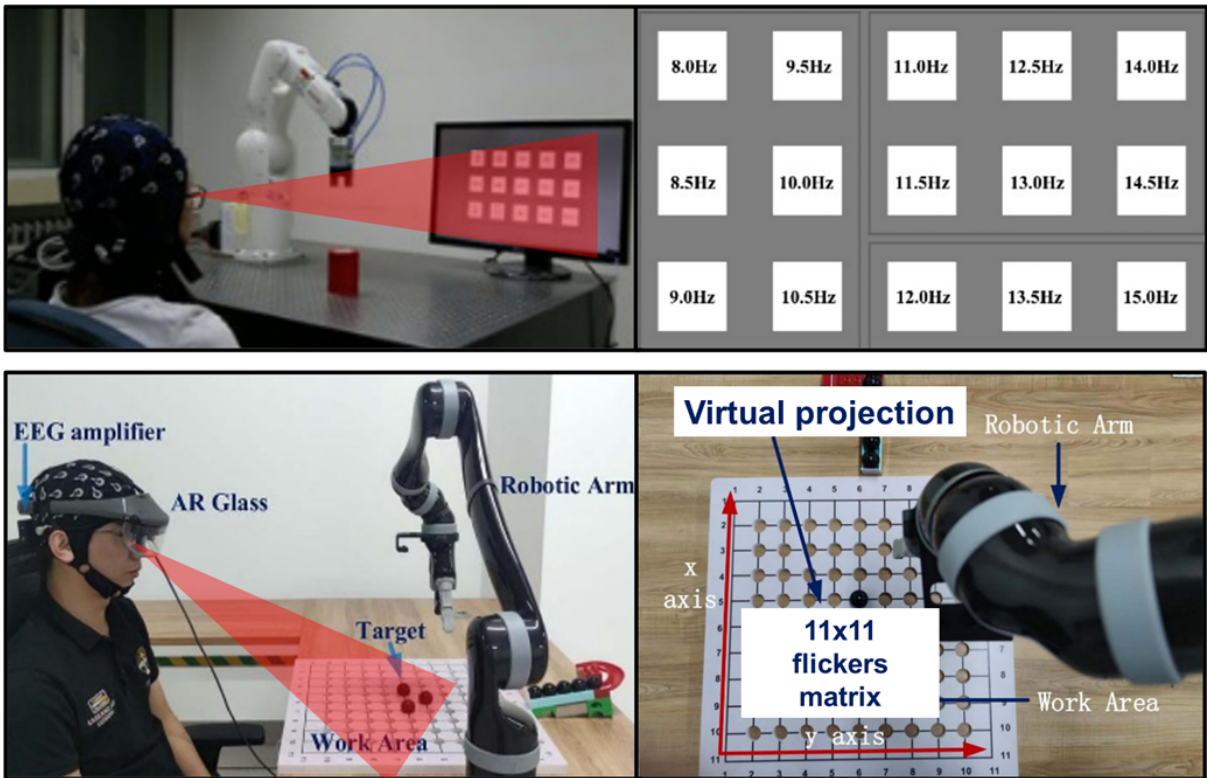


Figure 10. Top left: Robotic arm control SSVEP-based BCI system with an external graphical interface. Top right: All the positions that can be reached by the robotic arm are mapped onto a monitor as SSVEP flickers of distinct frequencies (adapted from Chen et al., 2018). Bottom left: Augmented Reality (AR) implementation of a robotic arm control SSVEP-based BCI. Bottom right: A matrix of flickers corresponding to all reachable positions is virtually projected and directly superposed to the working area (adapted from Chen et al., 2021).

Eventually, one last attentional-related issue refers to the pacing implementation details. BCIs can be classified into asynchronous (self-paced) and synchronous systems. Asynchronous BCIs, like most aBCIs, allow users to control the device at their own pace without relying on specific timing. In contrast, synchronous BCIs require users to generate specific neural signals at predetermined times as dictated by the system. Although synchronous BCIs offer advantages such as faster and more accurate control over devices, they present several disadvantages that may affect users' attentional abilities. One of the main challenges with synchronous systems is that users need to adjust to a predefined time frame of stimuli presentations, reducing their sense of control. With a synchronous system, the pace of text entry is regulated by the computer, not the user. For example, in a P300 speller, users must wait and remain focused until the expected rows and columns are flashed. This is also true for most SSVEP-based BCIs. For instance, Mannan et al. (2020) used a sound to indicate when the participants could glance at the flickering letters to type them. In some cases, the activation time of the synchronous BCI can too fast (eg. 350ms),

particularly for untrained users (Ma et al., 2018). This short activation time, while allowing for highly responsive BCIs, does not allow users to check the validity of the last input before moving to the next one. This can be mentally taxing and distracting, leading to reduced attentional abilities over time and false activations (i.e., typo errors). As a result, users may become preoccupied with the timing and execution of the signal rather than focusing on the task at hand.

5.3 Visual comfort

As discussed above, SSVEP-based BCI uses visual flicker that may distract the user from the task at hand. The intensity of these flickers is maximized to enhance the responses recorded in the brain and increase classification accuracy (Zemon, 2006, Wu & Lakany, 2013). Prolonged exposure to these repetitive stimuli has reportedly been linked with several inconveniences whose severity ranges from minor visual discomfort to lasting eye strain, from induced mental fatigue to consequential episodes of drowsiness (Zhu et al., 2010). Moreover, the presentation of high-intensity visual stimuli over a certain range of frequencies poses a risk of triggering epileptic seizures in photosensitive individuals (Fisher et al., 2005). All these issues diminish the usability and retention of rBCI solutions. The following paragraphs present solutions for the design of non-intrusive rBCI.

Several properties of visual stimuli used in SSVEP paradigms can be modulated to resolve the aforementioned issues. First and foremost, to reduce photosensitive hazards and visual fatigue, the range of frequency used can be adapted. Typically, the visual stimuli are flickered between a 4-20 Hz range due to hardware limitations (e.g., common monitors with limited refresh rates) and higher signal-to-noise ratios (SNR) at these specific frequencies. One solution to this issue is to increase the flickering frequency to make these flashings visually transparent to the user (Ladouce et al., 2022). Ladouce et al. (2022) reported that visual stimuli with high flickering frequencies were deemed as more comfortable visually and less intrusive by the participants. While the use of higher frequencies for the design of SSVEP flickers may seem like a promising solution from a user experience perspective, the loss of signal-to-noise ratio renders this approach impractical for BCI applications as a significant drop in classification performance was observed as a function of stimuli frequency (especially above 30Hz). Diez et al. (2011) and Muller et al. (2011) demonstrated the relevance of high-frequency flickers through the use of LEDs arrays flashing from 37 to 40Hz. Extending the complexity of the classification to

an 8-class problem, Chabuda et al. (2018) used 30 to 39 Hz RVS in an online BCI speller which achieved an average accuracy of 96%. Ajami et al. (2018) also report high classification performances (98.4% for 30–35 Hz, 99% for 35–40 Hz and 95.2% for 40–45 Hz) in a 5-class problem in an online BCI application with LED used as SSVEP generators. It is, however, important to note that such classification performance was attained using a long epoch length (up to 10 seconds) which severely limits the responsiveness of the interface and induces user frustration (Ladouce et al., 2022). More recent studies have applied offline analysis on 2 s epochs, and Liang et al. (2019) reported 91% classification accuracy on a 40-class BCI paradigm using 30 to 36Hz RVS, whereas Yue et al. (2020) reached 87% with only 1 s epoch length using 31 to 40 Hz.

A second solution to improve user experience and visual comfort is to reduce the contrast and intensity of RVS by lowering their amplitude depth. Stimulus amplitude depth refers to the contrast difference between the two antagonist states of an RVS. The mean luminance intensity is also reduced as the maximal luminance reached is lowered. In most SSVEP-based BCI implementations, the amplitude depth used is maximal. This practice aligns with findings from research on the visual system highlighting the sensitivity of primary visual cortical areas (V1) to high contrast stimuli (Wandel, 2017) and larger foveal magnification in response to high luminance visual information. In a recent study, Chang et al. (2014) investigated the relevance of Amplitude Modulation (AM) for RVS to reduce eye fatigue. The AM approach consists of modulating the amplitude of the flickering signal by another oscillating signal of higher frequency (the carrier) over time. The authors concluded that AM, although leading to reduced stimuli intensity on average, was only merely perceptible to the users and did not improve visual comfort. It is important to distinguish the Amplitude Modulation approach from RVS amplitude depth reduction.

Moreover, AM modulation implies an increase in the spectral complexity of the SSVEP signal, which decreases classification performance. In another study (Ladouce et al., 2021), the authors demonstrated that a 90% reduction of the maximal amplitude depth significantly improved visual comfort. Although diminished compared to full amplitude depth RVS, the classification accuracy was still around 80% for a 4-class problem (using a 3s window length). These studies sparked interest in amplitude depth reduction to improve RVS visual comfort and overall user experience during SSVEP-based BCI control. In a recent study (Ladouce et al., 2022), the trade-off between flicker contrast (amplitude modulation depth) and classification performance was further investigated, showing

promising results for low (40% of maximal amplitude modulation depth) contrast flickers in an online T9 SSVEP-BCI application. Adopting a similar approach for code-VEP stimuli could enhance visual comfort since their aperiodic presentation is generally less visually taxing than SSVEP stimuli. Adjusting parameters such as amplitude, depth modulation, pacing, and duty cycle can reduce the amount of light presented during code-VEP stimulation, resulting in a more comfortable visual experience for participants.

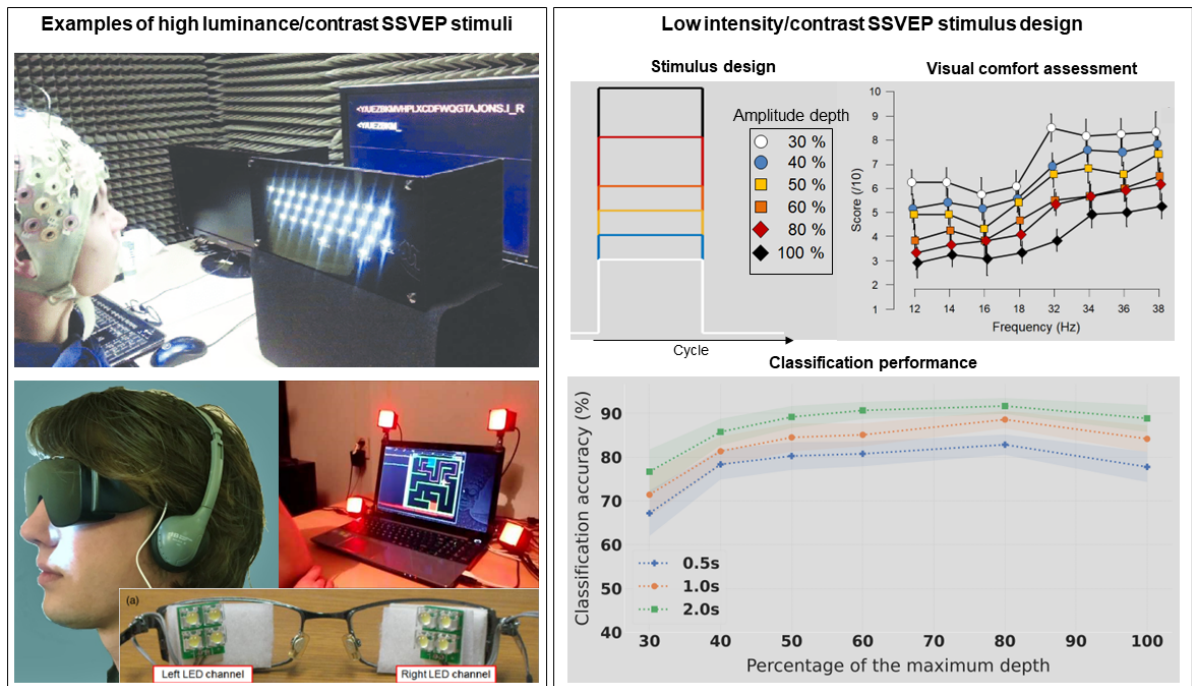


Figure 11. Left: Illustration of current practice in SSVEP-based BCI research to maximize SSVEP responses signal-to-noise ratio through the presentation of high luminance, high contrast visual stimuli as close as possible to the user's retina (elements adapted from Won et al., 2014; Lim et al., 2013). Right: Ladouce et al. (2022) study highlighting that reducing amplitude modulation depth (contrast and luminance of SSVEP stimuli) leads to improvements in user experience (notably visual comfort) at a minimal cost in terms of classification performance.

5.4 Sensors and physical comfort

Most non-invasive EEG-based BCIs require a conductive gel on the user's scalp to allow conduction with the electrodes and a good signal-to-noise ratio. These systems have a long setup time and require users to clean their hair after each utilization.

These several drawbacks prevent their use in an everyday-life setting. Dry-electrode EEG systems might help overcome these issues though they display a lower signal-to-noise ratio than traditional wet/gel electrodes. For instance, several studies conducted out of the lab have successfully shown the potential of wireless dry EEG systems to detect critical operators' states (Dehais et al., 2018; Callan et al., 2018, Scholl et al., 2016) even with very

few electrodes (Dehais et al., 2019b, Somon et al., 2022, Getzmann, 2021). However, despite their convenience, dry EEG systems are not always comfortable for users. Indeed, these dry electrodes require tight-fitting to maintain good contact with the scalp as they are more sensitive to movement or artifacts than those used in traditional EEG systems. This can cause pressure points, which may lead to soreness or even headaches, particularly if the sensors are worn for extended periods. Individuals with thick hair may have difficulty achieving good contact between the sensors and the scalp, resulting in discomfort and reduced data quality. When using dry EEG systems, individuals with dry or flaky scalps may experience irritation or discomfort. Similar issues have been reported with fNIRS systems, especially with high coverage (Pinti et al., 2020).

In recent years, the development of neurotechnological hardware has led to an expanding range of unobtrusive sensors like hear-EEG or around-the-ear EEG (e.g., cEEGrid) and low-cost devices, such as the Emotive, Dreem, OpenBCI, and the Muse system aiming at everyday life applications (see Figure 7). These systems are affordable, lightweight, small, and user-friendly, with a simple setup process. Some have embedded electrodes in glasses, headphones, helmets, or VR head-mounted displays. This makes them ideal for field research, remote monitoring, or at-home use. Several studies indicated the potential of these unobtrusive devices for mobile research (Cannard, Wahbeh & Delorme, 2021; Krigolson et al., 2021; Krigoloson et al., 2017, Hölle et al., 2022, Getzmann et al., 2021) and the development of brain-computer interface (BCI) as shown by Simar et al., (2020). While these systems offer better comfort for the user, these low-cost systems have a limited number of electrodes. These issues prevent using advanced signal processing techniques to address noise and artifacts in the signals (Dehais et al., 2023). Nonetheless, dry-electrode EEG systems are a promising area of research with the potential to revolutionize the field to push BCIs out of the lab.



Figure 12. Examples of unobtrusive EEG sensing systems for BCI applications. A: Dry EEG sensors embedded in glasses frames (adapted from Sopic et al., 2018). B: Headphones-mounted wet-sponge EEG electrodes (Smartfones from mBrainTrain, Serbia). C: In-ear electrodes (adapted from Bleichner et al., 2015). D: Dry EEG extension of a Virtual Reality headset (Galea from OpenBCI, New York). E: Prototype of a flight helmet fitted with EEG sensors (red dots represent possible electrode locations inside the helmet). F: Around-the-ear EEG array (adapted from Bleichner and Debener, 2017).

5.5. Design Issues

BCI systems are rapidly evolving, and some BCI designs translate from research into practical use to serve clinical (e.g., ALS patients) and healthy (e.g., gamer) populations. However, traditional BCI development still only focuses on enhancing technical aspects, including signals processing to improve classification performance and miniaturizing hardware, without properly considering the final user's needs (Lu et al., 2021). The usability of the overall BCI system and human-centered design have yet to be the guiding principle in constructing the user interface and selection. This gap can be addressed by including the user-center-design (UCD) approach to address the BCI user satisfaction issue (Kübler et al., 2014). In addition to the traditional evaluation of BCI accuracy and time processing, UCD applies ergonomics and user-subjective measurements such as effectiveness, efficiency, and satisfaction to evaluate the device. Within this context, instead of building a BCI system and testing its utility, the BCI designers should first consider the users' needs, then propose a system that addresses those needs. Based on the user's evaluation, the designers would improve and test the system again. After a few interaction cycles, the system would be expected to reach a more mature and satisfactory level.

Several demonstrations of such BCI development using a UCD approach have been performed. In a BCI case study of a participant with severe motor and communication deficits, the application of the UCD approach demonstrated that considering the user's

specific needs created alternative ways of BCI applications (Schreuder et al., 2013). Also, USD was applied in a comparison study of the brain painting and the P300 BCI paradigms in a sample of four participants with severe disabilities (Zickler et al., 2013). ALS patients, caregivers, and professionals were evaluated to contribute to BCI applications based on the UCD approach (Liberati et al., 2015). Applying the HCI principles and expertise to the BCI design process is a promising new approach to enhance the overall satisfaction of BCI users.

6. Social and ethical issues

A comprehensive review of the literature regarding brain-computer-interfaces (BCI) and social research (Kögel et al., 2019) concluded that while feasibility aspects of BCI have been being studied extensively, comparatively little in-depth research was conducted on the self-image and self-experience of the BCI users. Most of the relevant quantitative studies investigating BCI users' opinions focused on 1) usability in terms of ease of use, fatigue/exhaustion, usefulness, acceptance, comfort, or safety; 2) performance measured in terms of accuracy, information transfer rate (ITR), subjective level of control, or skill development; 3) satisfaction; 4) psychological factors such as motivation, mood, depression, memory, and attention or concentration; 5) workload assessed in terms of efficiency; and 6) the quality of life. Published studies on the caregiver's perspectives and expectations towards BCI technology identified such issues as the considerations of an opportunity to maintain communication between caregivers and caretakers, the opportunity of "back communication", as well physical, psychological, social barriers for BCI applications, and BCI potential in terms of freedom and independence (Kögel et al., 2019).

The development and the wide-scale deployment and application of BCI technology should be guided by robust ethical standards that concern the use of bio-signals, appropriateness of technology, privacy, end-user experience, distributive justice, and legal liability issues (Beauchamp & Childress, 2009; Haselager et al., 2009; Farah, 2011; Padfield et al., 2019; Zabcikova et al., 2022). Vlek et al. (2012) discussed the ethical issues related to the application of BCI for users with disabilities and healthy users and observed that BCI technology's expectations are important at different levels, ranging from individual users to legal representatives to the public (via the media). Burwell et al. (2017) reported that BCI research generates significant ethical, legal, and social concerns, including the issues of humanity and personhood, stigma, autonomy, privacy and security,

research ethics, safety, moral and legal responsibility, fair access, and justice. It was pointed out that future research should focus on developing practical solutions to the ethical challenges of BCI, facilitated by the collection of empirical data on the perspectives of BCI shared by the general public, BCI users, and BCI researchers. Tamburrini (2009) identified specific ethical issues that arise concerning healthcare applications and other prospective uses of BCI communication technologies in education, entertainment, workplace organization, security, and training (Table 1). The related issue of BCI illiteracy and its remedies have also been discussed in the subject literature (Vidaurre & Blankertz, 2010; Grübler et al., 2014; Lee et al., 2019).

Recently, Wolpaw et al. (2020) observed that the success of BCI technology depends on the effective management of the complex administrative and clinical demands of human research, including the distinctive ethical issues involved in BCI research and development. Furthermore, Coin et al. (2020) pointed out that the emerging applications of novel BCI technologies, such as brain-to-brain interface (BBI) or computer-to-brain interfaces (CBI) that are focusing on commercial ventures that seek to combine human intelligence with AI, pose new and unique ethical concerns (Haselager et al., 2009; Grübler & Hildt, 2014). Table 2 provides an overview of some of the primary ethical challenges and the motivation for subjects participating in the BCI studies, as outlined by McCullagh et al. (2014). Furthermore, Table 3 summarizes the ethical guidelines for BCI development and deployment. The main categories of these guidelines refer to governance structures, the consent process, knowledge transfer, experimental issues, consequences of success or failure, and risk mitigation.

Table 1. Ethical issues in healthcare and other prospective uses of BCI (after Tamburrini, 2009).

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- What is the binding value of informed consent, and last will that locked-in patients express using a BCI?
 - Who is responsible for damages caused by a brain-actuated mobile robot?
 - Is human dignity jeopardized by unconscious or pre-conscious brain information processing in BCI-enabled, human-machine cooperative problem-solving?
 - Are worker rights threatened by the use of BCI alertness detectors in intense workflow situations?
 - Should one allow the plastic brain of young people to interact with BCI-controlled computer games?
 - Does motor and mental enhancement by brain-robot networking affect user persona?
-

Table 2. Ethical challenges and the motivation for subjects (after McCullagh et al., 2014).

A. Research investigators as subjects

Motivation: The participant will be fully committed to the research project. He/she will normally have no physical or EEG impairment. The participant may, however, be biased and unduly motivated and cannot be taken as representative of other volunteers. Hence performance results obtained could be optimistic for the wider community.

Main potential ethical concerns: Data security

B. Healthy volunteers:

i) Undergraduate student as investigator/subject. Motivation: The participant will be partially committed to the project, but this may be time limited. He/she may need to obtain results from a small experiment as part of an undergraduate qualification. However, when this goal has been achieved, the participant is unlikely to be available.

ii) Postgraduate student or research company volunteer as a subject. Motivation: The participant will usually have some scientific interest and commitment to research. He/she may be induced by a small stipend to take part. The participant will normally be cooperative and fully engaged with the experiment. The duration of the recording sessions may impinge upon the participant's valuable time. The above can adversely influence the willingness for re-testing.

Main potential ethical concerns.

Data Security: Coercion by a supervisor or the need to participate should be addressed.

C. Public volunteers as subjects

Motivation: The participants may be recruited as a control for the intended user group under study. They may be in an older demographic (over fifty, for example, age-matched). As such, they may have little computer or experimental experience and find the process unpleasant and possibly tiring or stressful. Alternatively, the participant may be reached at a scientific exhibition (e.g., CEBIT). In this case, the protocol must minimize time interaction.

Main potential ethical concerns. Data security. Additional ethical issues will depend on the volunteer, e.g. privacy may well be an issue.

D. Vulnerable subjects Brain injured participants who are (i) living in a sheltered 'smart home', and (ii) living independently in the community.

Motivation. The participants may have varying commitments to the project. He/she may participate with initial enthusiasm. If the results are not positive, then frustration can reduce motivation. A caregiver may be involved in the ethical process for consent.

Main potential ethical concerns.

Potential ethical issues include confidentiality, privacy, raised expectations, and stress and fatigue associated with the recording. Obtaining fully informed consent and the right to remove consent for participation becomes important, and this should be actively managed.

Table 3. A summary of ethical guidelines for BCI development and deployment (after McCullagh et al., 2014). Note: A,B,C and D refer to participants categories defined in Table 2.

Governance Structures

- In a consortium, establish an *Ethical Advisory Board* with participation from each partner and a trusted external adviser. Where internal agreement cannot be reached, the external adviser should have the final say on ethical matters that impact upon subjects.
- Enforce team responsibility so that any user issues are reported via the EAB. This includes reporting any negative side effects to users.
- Ensure that the EAB reports at consortium meetings and review meetings.

The Consent Process

As part of the consent process, the following should be disseminated to the user (and their representative, if in a vulnerable group) to manage user expectations:

- Emphasize the research nature of the BCI study. Indicate that some of the work is exploratory in nature to allow new algorithms and approaches to be developed and tuned.
- Do not raise expectations unduly. BCI is complex and does not work for everyone. Explain that, at this stage, the BCI may not perform consistently and possibly not at all.
- FP7-BRAIN experience has shown that BCI is less likely to work for a person with brain injury. This should be made clear to potential subjects, although the issues for this performance are complex.
- Confirm that BCI is not a therapy (at this stage of development).
- Ensure that the users know they can halt the experiment at any time if desired and have an agreed way that a communication-impaired user can signal this. This should address continued consent.

Knowledge Transfer: Training is required for both participant and carer responsible for BCI setup; thus, usability is crucial.

- Make the recording procedure as straightforward as possible from the users' perspective. Software that requires complex libraries (e.g., for signal processing) should be automated using an installation wizard.
- Provide quality documentation. This should include a list of all components within any deliverable, with version number and updates noted, supplied with a user guide document for the system component. Video guides should also be considered, which can be aided by screen capture software.
- Remove features irrelevant to those conducting experiments (i.e., debug information).
- Utilize appropriate communication tools (remote desktop control and videoconferencing) for frequent interaction between sites.
- Provide continued technical support to those conducting experiments with a limited understanding of the scientific process.

Experimental Issues: For widespread deployment, set up time, subject comfort, and aesthetics are relevant issues.

- Build ethical requirements into the experimental specification. These include the subject's comfort, the setup time, and the duration of a recording session (which may be tailored to the needs of the user group).
- Design software to facilitate user rest breaks.
- Determine a minimum level of reliability for using with vulnerable subjects.
- Proven stability and effectiveness are needed using evaluations with groups A & C before experimentation can involve group D.
- There is a need for a stable system for data capture.
- Refrain from allowing project deadlines to result in the premature delivery of software.
- Software may need to be tuned to a subject, but it should never be 'debugged' on a vulnerable subject.
- A minimum user accuracy should be established in calibration, e.g., 75 %, before more complex interaction, e.g., with a virtual environment (to reduce potential user frustration).
- Clinical hygiene standards should be employed to guard against infection (e.g., cleaning of electrodes, disposable sponge electrodes).

Consequences of Success or Failure: Consideration concerning the user's expectations is needed.

- Apply efficient screening to identify subjects more likely to benefit from BCI technology.
- Establish guidelines before evaluation to help determine how experimentation should be halted due to low performance and determine how this should be managed.
- Indicate that failure to use a BCI successfully is not a reliable indicator of the subject's medical condition.
- The decline in a user's performance may require reporting to a suitable profession for a clinical review.

Risk mitigation:

- Predict likely risk and adopt procedures to protect against the risk wherever possible.
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7. Conclusion

The area of Brain-Computer Interfaces (BCIs) is a rapidly growing area of research with a great variety of applications in both medical and non-medical fields, mostly due to their versatility and ease of use (Berger et al., 2007; Van Erp, Lotte & Tangermann, 2012; Shih et al., 2012; Wolpaw, 2013; Martini et al., 2020). The BCIs also hold immense promise to enhance human-machine symbiosis in everyday life situations, as the main BCI principle is to use "thoughts" for control purposes (Mak & Wolpaw, 2009; Gao et al., 2021). However, the design and development of BCIs have been predominantly led by researchers with backgrounds in computer science and engineering while overlooking important end-user issues. Furthermore, BCI research tended to focus on technical accuracy, leading to a lack of understanding of the real-world impact of BCIs on end-users. The above has resulted in limited adoption and usability of BCIs among individuals who would benefit from them the most. Therefore, it is crucial to involve the Human-Computer Interaction (HCI) community in the design and development of BCIs. Also, despite its rapid development, BCI systems tend to be "alive" only in laboratory environments, and the progress of the output of these systems into the realities of everyday life is still slow. There is also a lack of trust in brain-computer interfaces in society.

Another issue with the BCI systems is that they require some initial training to be efficient (Curran & Stokes, 2003; Buttfield et al., 2006). This is why the HCI can benefit the design of BCI systems by providing a user-centered approach to design, helping to overcome technical challenges, and contributing to ethical and social considerations (Zickler, 2013; Kübler et al., 2014). Integration of HCI and BCI can lead to the development of more effective, user-friendly, and responsible BCI systems (King et al., 2022; Han et al., 2022). First, HCI can facilitate a user-centered approach to design to ensure that BCI systems are intuitive and easy to use and meet the user's needs. HCI

methods, such as user testing and usability evaluations, could be used to assess the effectiveness and efficiency of BCI systems (Mühl et al., 2014). HCI can also provide expertise in designing appropriate interfaces to facilitate desirable user-system interactions.

Additionally, HCI can provide guidelines for effective feedback mechanisms that help users to learn how to master any BCI systems (Tan & Nijholt, 2010). Finally, HCI can contribute to BCI design's ethical and social considerations. As BCI technology becomes more widespread, it is important to understand the implications of this technology on privacy, autonomy, and social interaction (Schick Tanz et al., 2015; Padfield et al., 2019; Zabcikova et al., 2022). HCI can provide insights into how BCI technology can be designed to respect the user's autonomy and privacy and how it can be integrated into society responsibly and ethically. Finally, HCI can benefit from BCIs to better understand the relationship between performance, brain, and technological environment.

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