BCI Innovation at the Intersection of Restoration, Augmentation, and Intelligent Systems

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ABSTRACT

Brain-Computer Interface (BCI) research and development (R&D) is regularly segregated by application: one set of labs and studies focused on BCI for restoration of lost function for clinical population, and often distinct labs and studies focused on BCI R&D to augment the performance of healthy individuals. In this paper, we set out to explore and outline how BCI innovation is now at the intersection of these two R&D targets, and how intelligent systems R&D is critical to both. This perspective is presented in the context of six principal axes for BCI R&D common to restoration and augmentation: invasiveness (invasive vs. non-invasive neural interfaces), intentional control (active vs. passive BCI), anthropomorphism (anthropomorphic vs. non-anthropomorphic perception and control), multiplexing (BCI only vs. concurrent natural and BCI perception and control), inclusion of peripheral measures (non-neural signals), and integration with intelligent systems.

Keywords: Brain-Computer Interface (BCI), Brain-Machine Interface (BMI), Neuroscience, affective computing, mental state monitoring, human enhancement, human-machine interaction, artificial intelligence

1.0 OBJECTIVE

Brain-Computer Interfaces (BCIs) bypass our natural pathways for interacting with the environment and technology through direct, real-time connections between the nervous system and computers. BCI research is flourishing in clinical settings: when accident or disease causes severe impairment, function can now be partially restored with BCI. Over the last decade, another significant BCI research and development (R&D) thrust focusing on healthy users has emerged with the goal of using neural interfaces to augment or amplify natural modes of perception, control, and mental state monitoring.

R&D for these two classes of BCI – restoration and augmentation – are most often considered, executed, and reported on separately. While the majority of the research projects at even our own organizations still focus exclusively on either restoration of impaired function for clinical users or augmentation for unimpaired users, we propose that a more integrated approach to BCI R&D is needed to achieve both restoration and augmentation goals, especially in the context of important enabling technologies like Mixed Reality (XR) and Artificial Intelligence (AI). We develop this perspective along six principal axes for BCI R&D common to restoration and augmentation: invasiveness (invasive vs. non-invasive neural interfaces), intentional control (active vs. passive BCI), anthropomorphism (anthropomorphic vs. non-anthropomorphic perception and control), multiplexing (BCI only vs. concurrent natural and brain-computer interfacing), inclusion of peripheral measures (i.e. non-neural signals), and integration with intelligent systems.

BCI has been recognized as an increasingly-relevant emerging technology for government applications ranging from health to national security [1-3]. In recent years, an unprecedented level of investment in BCI has been observed across government and industry alike. Here, we present recent results, demonstrations, and emerging use cases that illustrate both the common and unique challenges for restoration and augmentation, and the central role for integration with intelligent systems at a time when government and industry are more focused than ever on paving the way for high-impact clinical, operational, and commercial use cases.

2.0 AXES

To organize the discussion of BCI innovation at the intersection of restoration, augmentation, and intelligent systems, BCI R&D is presented along the following six axes or dimensions.

2.1 Invasive and non-invasive neurotechnologies

Traditionally, *invasive* BCI refers to those interfaces that require surgery (e.g., Microelectrode Arrays or MEAs), and reserved almost exclusively for clinical research and application. Direct access to the brain has its advantages. Traditional invasive modalities include electrocorticography (ECoG) placed on the surface of the cortex and MEAs that penetrate cortical tissue (Figure 1), which offer the best spatial and temporal resolution for both sensing and modulating neural activity, and translate to the relatively high-fidelity input/output to and from the brain needed to finely control individual fingers on a prosthetic hand [4], transmit detailed sensory information from that prosthetic to the brain [5], and even interpret the phonemic [6], and semantic [7] content of thought. Next-generation invasive modalities are under active development, from research teams across academia and industry pursuing new technologies as part of several recent Defence Advanced Research Project Agency (DARPA) programs to companies like Neuralink focused on basic research targeting more moderately-invasive surgical BCI techniques.

Traditional *non-invasive* BCI modalities include electroencephalography (EEG) and magnetoencephalography (MEG), which track electromagnetic neural activity, as well as functional magnetic resonance imaging (fMRI) and functional near infrared spectroscopy (fNIRS) which track hemodynamic neural activity from sensors placed on or near the skull. All existing non-invasive approaches have significant limitations in their temporal and spatial resolutions – translating into limitations in Information Transfer Rate (ITR) – and/or system portability. Whereas surgical approaches can begin to provide the spatial and temporal resolutions needed to productively encode and decode neural signals, non-surgical approaches have been mostly relegated to tools for basic BCI research and proofs-of-concept, rather than functioning modalities for BCI application. Emerging minimally-invasive surgical and high-resolution non-surgical techniques will enrich this landscape. To begin to approach the spatiotemporal resolution afforded by surgical approaches, academic and commercial organizations are developing new modalities like those being funded under DARPA's Next-Generation Nonsurgical Neurotechnologies program, as well as commercial efforts to build on existing technologies, like those in development at companies like Kernel.

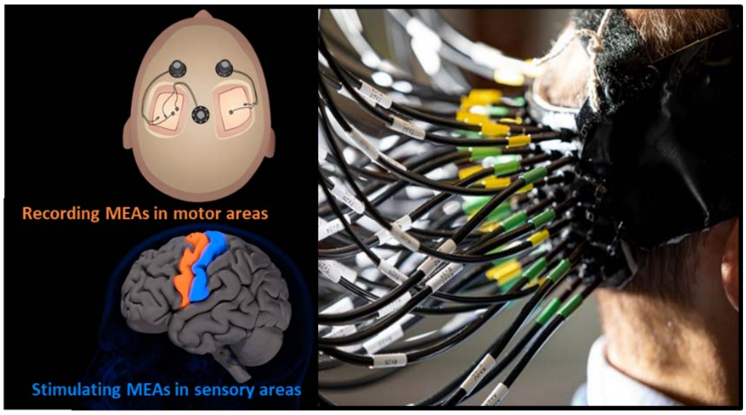

Figure 1: Emerging surgical and non-surgical neurotechnologies.

At left, an illustration of one of the most extensive chronic implants. MEAs in both the left and right hemisphere (shown here through the skull and scalp, and connected to external devices through pedestals mounted on the head) were implanted to both record activity in motor cortex and stimulate activity in somatosensory cortex. At right, a picture of a next-generation fNIRS system in development with high-density fiber optodes tiles the occipital cortex for visual field information extraction [8].

Historically, augmentation research for unimpaired users have been most associated with non-invasive modalities and invasive modalities have been most associated with functional restoration research for clinical use cases. Many research groups and most published studies focus on one or the other, but many of the advances over the next decade will involve innovation at the intersections. Invasive research with clinical participants charts the path for non-invasive approaches and use cases: clinical research with more powerful invasive modalities is critical for discovering and evaluating the upper-bounds of what may be possible, uncovering new augmentation use cases and encoding and decoding techniques to be translated for non-invasive modalities as they improve. With the knowledge gleaned from invasive studies to best define the targets for non-invasive recording and stimulation, non-invasive modalities will increasingly be able to replace surgical BCI solutions for clinical populations. These advances will only be accelerated by more attention to the intersections of invasive, non-invasive, restoration and augmentation research.

2.2 Active and passive BCI: From intentional control to monitoring

When looking across the landscape of BCI, another primary axis of variation has been *active* control and *passive* monitoring. Most BCI research and applications are considered active, and refer to tasks and applications that involve intentional, conscious, often effortful involvement of the individual, like controlling a prosthetic arm or moving a cursor. Passive BCIs function without the need of intentional or effortful control [9], and typically target adapting systems in real time to a user's detected cognitive workload, attention, fatigue, response to unexpected events, or to predictions of a user's intended movements. Examples of possible system adaptations are the decrease of information flow to a user or the increase of level of automation if the user is found to be overloaded; repetition of information that is likely to have been missed; and a suggested or imposed break when fatigue is detected. Estimates of how a user is going to move based on neural activity can be of use for mixed reality, exoskeletons, and other applications that rely on real-time updates to movement. Integrating passive information from brain signals across multiple individuals can be used to track and respond to a group's attentional engagement over time [10, 11].

Figure 2. Examples of passive BCI.

At left: Predicting head rotation through passive BCI may improve real-time video streaming in Head Mounted Displays [12]. At centre and right: Passive BCI can differentiate between high and low workload in a pilot during real flight [13], and detect the probability of pilot-induced oscillations [14] using EEG systems like the one shown at right.

While there are still many challenges for realizing these applications – generalization across individuals and contexts, performance under real-world conditions, and the form factors and usability of BCI equipment, to name a few – the goal in all of these examples of passive BCI is to augment human performance. Passive BCI has been a more compelling target for augmentation research for unimpaired users, where opportunities for BCI-enabled active control must compete with good options for active interfaces, like keyboards, joysticks, and language. The information transfer rate of active (non-invasive) BCI remains low compared to what can be reached when common modes of communication can be used (i.e. muscle activity), and attentional burden is high. For healthy users, there has not yet been a clear value proposition for replacing an existing, well-functioning channel of communication through BCI, or adding a channel for intentional communication [15]. However, passive BCI – using spontaneously generated brain signals as recorded during task performance as additional information that would otherwise not be available – could augment performance.

In contrast, functional restoration research has focused almost entirely on active BCI, where the value proposition has been obvious, and applications involving passive BCI have been rare (though see [16] for a discussion of passive BCI for memory impairments). Still, information on workload or mental effort, fatigue, engagement and emotion in patients can be used to more effectively personalize and adapt treatment, especially if patients cannot express themselves well verbally. Active functional restoration BCIs can be blended with augmentation-focused passive BCIs to improve performance, for example, using passive signals related to error to identify and correct behaviors of the active BCI that were not intended by the user [17].

Augmentation is more clearly achieved through passive BCI – especially for augmented human-machine interaction – while functional restoration is more clearly achieved through active BCI. However, as the ITR for non-invasive modalities improves, so will the potential augmentation use cases for active BCI. It should also be noted that there are many functional restoration-inspired active BCI use cases for healthy users working under extreme operational constraints. For example, specialists involved in Chemical, Biological, Radiological, Nuclear, and Explosive (CBRNE) operations often work with protective gear and under conditions that limit mobility, dexterity, and verbal communication. The value proposition of active BCI for these populations may closely resemble that of clinical populations.

2.3 Anthropomorphic and non-anthropomorphic BCI

Much of the functional restoration BCI research has focused on *anthropomorphic* perception and control –to restore impaired or lost sensory or motor functions, like the perception and control of robotic prosthetic limbs that resemble natural limbs in both form and function. Alternatively, *non-anthropomorphic* BCI research attempts to provide perception or control of devices and systems that bear little resemblance to the natural senses and motor system, like sensing infrared light or controlling an aircraft (Figure 3).

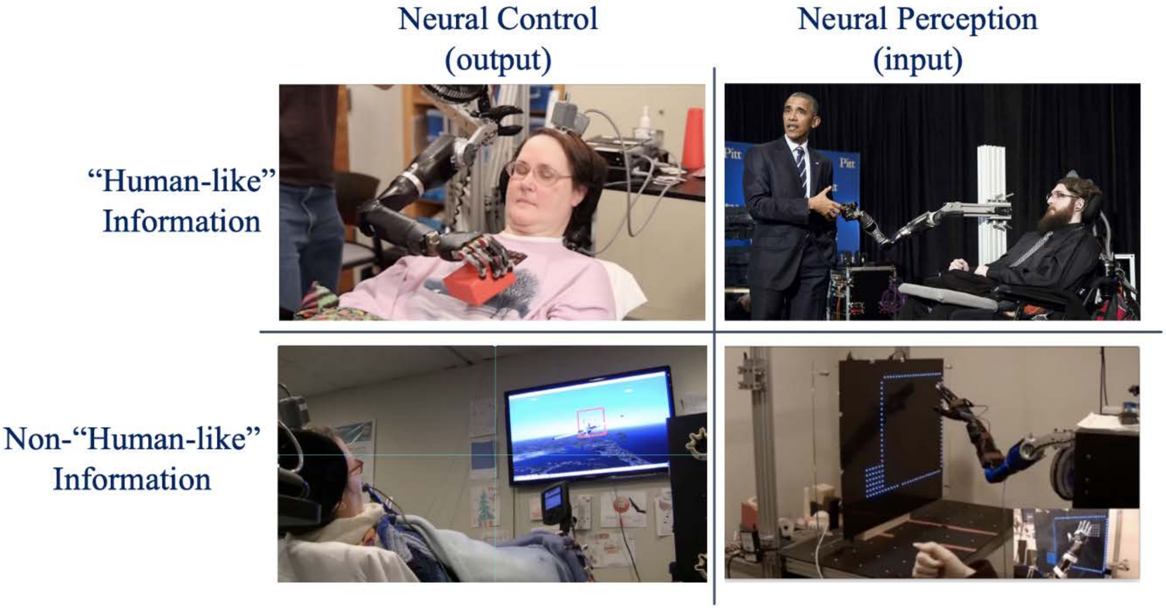

Figure 3. Anthropomorphic (human-like) and non-anthropomorphic perception and control.

Clockwise from upper left: Participant with a chronic motor implant controls the anthropomorphic prosthetic arm and hand to feed herself chocolate; Participant with a chronic sensorimotor implant perceives anthropomorphic sensations from the prosthetic fingers and hand during handshakes and fist bumps; Participant perceiving invisible infrared light through an infrared camera mounted on the prosthetic hand and set up to send information to sensory cortex as a demonstration of non-anthropomorphic perception; Participant intuitively controlling an airplane in a flight simulator as a demonstration of non-anthropomorphic control.

BCI offers the possibility of extending both perception and control beyond traditional domains for users to embody a range of systems. Critical elements for embodiment include "achievement of a certain kind of sensory/motor coupling" [18]; the broad range of objects or tools that can be embodied highlight the malleability of body representations. Incorporation of external objects into one's body schema requires several criteria, including ownership, agency, sensations, location, appearance, and response to stimuli. Embodiment is expected to reduce the effort needed to control a device and to improve performance [19] across anthropomorphic and non-anthropomorphic contexts, as well as restoration and augmentation use cases. For restoration of function, BCI-controlled prostheses should feel like natural extensions of the self, but other non-anthropomorphic use cases in development, like wheelchair and automobile control for clinical populations and teleoperation for non-clinical populations, will similarly benefit from BCI-enabled embodiment.

2.4 Neural multiplexing

Many of the most significant innovations in recent BCI research have been in the context of spinal cord injury, severe paralysis, and amputation. As an artefact of this focus, work has largely ignored one of the most critical research gaps for broad application: whether the brain can simultaneously accommodate both

BCI-enabled and native perception and control. For example, can you use your own hands and senses while simultaneously using a neural interface, and what are the cognitive and neural limits?

The extent to which physical movements and BCI control interact is poorly understood, but the limited data available suggests that the mental processes associated with each will interfere with one another. For example, controlling a computer cursor through decoded neural activity while naturally using a part of the body causes encoding and decoding algorithms to fail, and communicating through a BCI while concurrently performing another task drastically decreases BCI performance [20]. Encouragingly, there have been some preliminary demonstrations of multiplexed control with ECoG [21]. If BCIs are to realize their potential to both restore function in less severe clinical cases and augment native human capabilities, these interactions need to be fully characterized and overcome.

Recent work with a chronic implant participant uniquely suited to advance neural multiplexing research has resulted in several initial demonstrations of simultaneous natural and BCI-enabled perception and control. This participant had stimulating and recording electrode arrays implanted in hand sensorimotor cortex bilaterally while, importantly, retaining significant spared sensation and control of his hands, wrists and arms. Recent multiplexing experiments have also uncovered several surprising perceptual phenomena resulting from intracortical microstimulation during simultaneous native touch, including enhanced tactile sensitivity and illusory percepts [22, 23] (Figure 4).

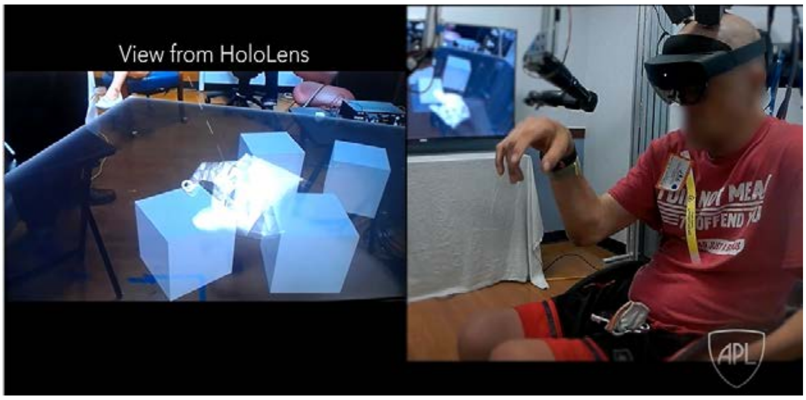

Figure 4. Multiplexing in mixed reality.

The participant uses natural arm and hand motor function to manipulate holographic objects in mixed reality while experiencing BCI-enabled percept in his hand and fingers. The visually identical holographic boxes shown at left feel different to the participant during manipulation tasks.

Neural multiplexing is one of the BCI research thrusts that will most benefit from more interaction between restoration and augmentation research communities. Neural multiplexing research will have implications for expanding the use of BCI to more moderately-impaired clinical populations, as well as applications to augment natural abilities that will rely on simultaneous native and neural interfaces.

2.5 Peripheral Measures

Brain signals are not the only sources of information about an individuals' intent or mental state: peripheral physiological measures like heart rate, electrodermal activity, and pupil dilation, as well as behavioral measures like eye movements and facial expression are rich sources of information to supplement, complement, or replace traditional BCI measures. These alternative measures are often less expensive, easier, and more reliable to record and analyze. For example, while selective shared attention can be monitored well through measuring interpersonal correlation between individuals' EEG [10,11], we recently showed that the same principle holds for heart rate and electrodermal activity, vastly expanding the range of possible applications [24, 25]. For certain types of information (particularly those related to arousal or affect), peripheral measures like electrodermal activity may even be more sensitive than direct neural measures. In addition, some BCI results (e.g., those associated with emotion classification in [26]) can be explained by artifacts that can be tracked with peripheral measure (e.g., facial muscle activity) [26].

Peripheral physiological and behavioural measures may serve as valuable complements to neural signals as part of multimodal or hybrid BCI systems that combine neural signals with other measures. As one hybrid example, peripheral signals can be used to place neural signals in context. Fixation- or saccade- locked EEG systems analyze EEG responses as a function of an individual's gaze [27]. This allows for distinguishing between 'looking at' and 'perceiving' or attending to the stimulus at the gaze location. Using this paradigm, we found that saccade-related EEG indicated whether observers were looking at a target they needed to remember as opposed to a non-target, whereas fixation duration and pupil size predicted whether they were actually going to remember the target [28] (Figure 5).

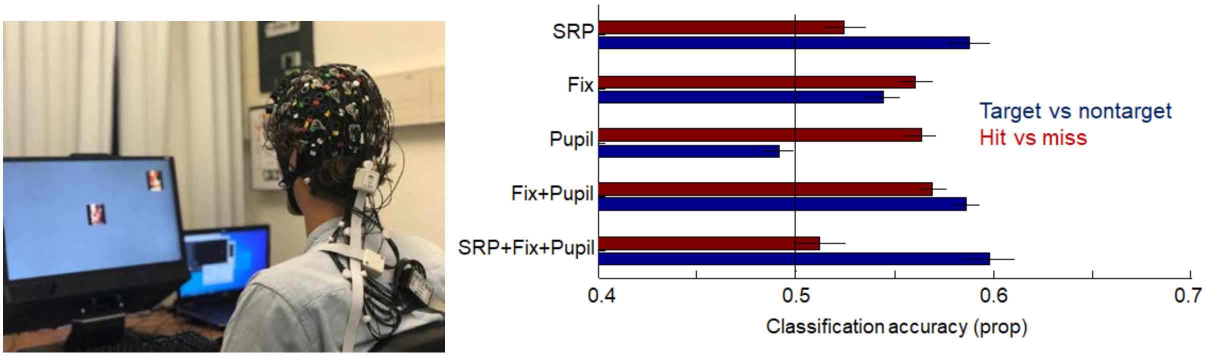

Figure 5. Combining neural signals with eye tracking.

Single-fixation classification accuracy for detecting whether the participant is looking at the target or not (in blue), and whether the participant will remember it later (in red) as a function of (multi-modal) brain, peripheral physiology and behavioural features: SRP (EEG saccade-related potential), fixation duration and pupil size.

Hybrid BCI systems that incorporate peripheral measures are beginning to impact BCI applications for both restoration and augmentation. Peripheral measures like EMG have been a focus for commercial applications like interfacing in mixed reality, and will grow as capabilities and form factors associated with peripheral measurement continues to improve.

2.6 Integration with intelligent systems

The most promising path to perceiving, deciding, acting and teaming in fundamentally new ways – beyond the reach of human intelligence or artificial intelligence alone – is through AI-BCI shared control. While AI will offer increasingly useful tools, without direct neural interfaces, human-machine teams will continue to be constrained by inherent sensory limitations (e.g. via voice, text, screens), motor limitations (e.g. via speech, keyboards, joysticks), and cognitive limitations (e.g. working memory, attention, biases).

A near-term challenge for neurally-integrating AI is how to interact with complex systems using relatively limited numbers of neural inputs [29]. As long as BCIs have limited ITRs, direct control (e.g. for spelling a word or controlling a wheelchair) will remain long and effortful. For example, the number of degrees of freedom for motor prostheses (like JHU/APL's Modular Prosthetic Limb) can be several dozen, which is about an order of magnitude more degrees of freedom than can be reliably decoded from non-invasive BCI today. AI can be used to reduce a high-dimensional problem to a small number of dimensions (like Google's autocomplete during search or suggested replies during texting), and fill in the gaps between the limited information from the brain and the information-rich controls needed for a complex system or machine (Figure 6). One team is researching methods to use the small number of available neural inputs (combined with other relevant context cues) to communicate high-level goals – like pick up the cup to a robotic arm, or follow that vehicle to a swarm – to an AI that can chain together primitive behaviors and perform the complex task needed.

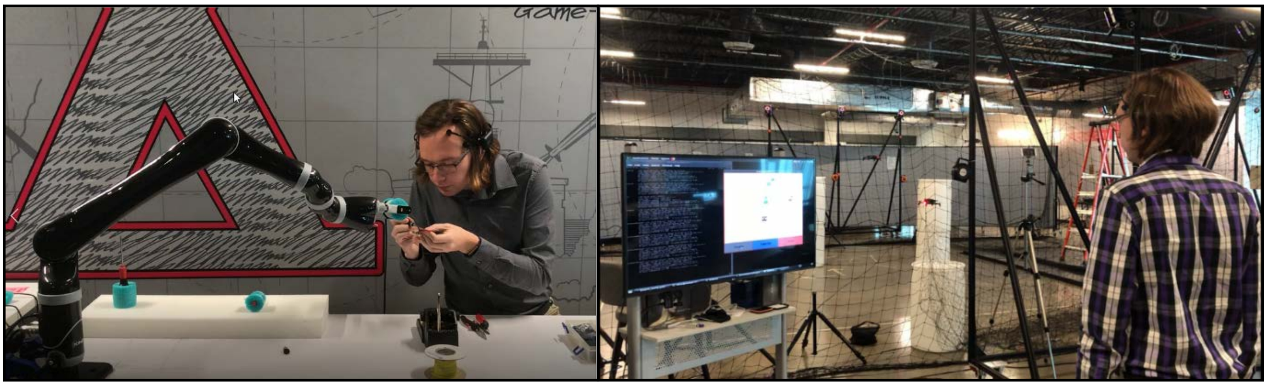

Figure 6. Prototypes for integrating BCI into intelligent systems.

An AI-enabled robot assistant (left) and a small swarm of AI-enabled quadcopters flown indoors (right) are taking high-level cues from the user via low-dimensional BCI to prototype new neurally-enhanced paradigms for human-machine teaming. At left, the operator's neural signals were used to step through a set of behaviors for a robotic limb that acted as a workbench-helper during a printed circuit board soldering task. At right, the operator's neural signals provided high-level goal locations and tactics (e.g., pursue or evade), and the AI provided the low-level quadcopter control.

A recent review [30] outlined different BCI approaches to control a humanoid robot for specific tasks like telepresence, handling objects, and navigation, distinguishing teleoperated modes where the user provides detailed commands, from autonomous modes of operation where the user provides high-level commands. When lower-level control functions are smoothly offloaded to AI under shared control paradigms, operator attention is freed up for higher-level cognitive tasks. For the foreseeable future, the details of the BCI modality and ITR, task demands, AI algorithmic progress, and other factors will be important for determining the best operating points on the sliding scale of shared AI-BCI control.

AI-BCI shared control is yet another area that has clear implications and applications for both functional restoration and augmentation, with the common goal of bringing BCI to bear in making the human-AI team more than the sum of their parts.

3.0 SUMMARY AND DISCUSSION

In this paper, we identify and review six primary axes or dimensions at the intersection of BCI R&D for functional restoration and augmentation:

1. **Invasive and non-invasive neurotechnologies.** Invasive research provides invaluable inputs for non-invasive concepts and modalities. Emerging minimally-invasive surgical and high-resolution non-surgical techniques will enrich this landscape.
2. **Active and passive neural interfacing.** ITR will continue to be a critical metric in evaluating the relative research goals and value propositions for active and passive BCI across restoration and augmentation use cases.

3. **Anthropomorphic and non-anthropomorphic perception, control, and embodiment.** When does a prosthetic, tool, or complex system start to feel like a genuine extension of the user, and to what effect? Invasive research suggests BCI may provide a unique tool to enable embodiment across anthropomorphic and non-anthropomorphic needs and restoration and augmentation use cases, from prosthetics to teleoperation.
4. **Neural multiplexing.** The ability to use the brain's natural mode of operation with the senses and muscles at the same time as a direct neural interface is critical for augmentation and many emerging functional restoration use cases.
5. **Peripheral measures**. These measures can supplement or complement neural measures as less-obtrusive alternatives, and as sources of critical contextual information (e.g., linking neural signals to gaze) for both restoration and augmentation applications.
6. **Integration with intelligent systems.** AI-enabled BCI helps to make the most of limited neural information, and offers new approaches to human-machine teaming at the speed of thought.

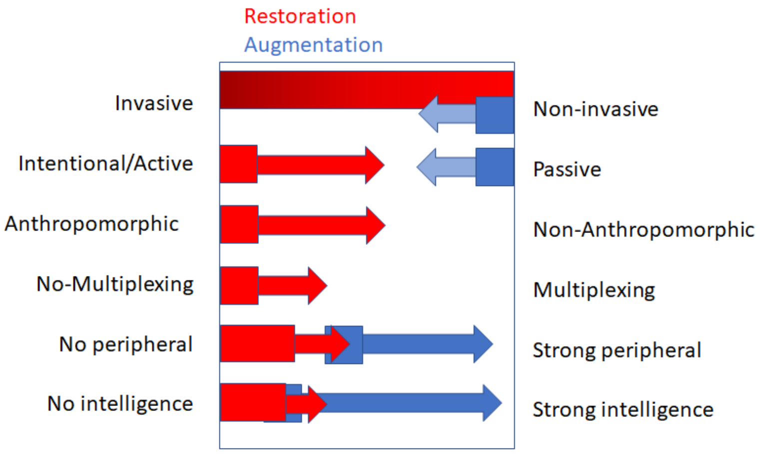

Figure 7. Estimates of historical status (blocks) and recent trends (arrow) for BCI research and application across restoration (in red) and augmentation (in blue).

Blocks represent estimates of historical representation, and arrows represent near-term trends. For example, research with invasive and non-invasive modalities have both contributed to functional restoration applications, non-invasive research has been the primary focus for augmentation, but invasive research is increasingly used to inform augmentation.

The vast majority of research questions and challenges across these axes are surprisingly common to restoration and augmentation goals. Recent trends in BCI research reviewed here (summarized in Figure 7) motivate significantly increased interaction between restoration and augmentation research programs. Until recently, all organisms have relied exclusively on their sensory organs to perceive information about the world around them, and their motor systems – their muscles, from forelimbs to vocal chords – to interact with their environments and one another. Neural interface research is creating pathways to directly access an individual's perception of the world, intent, and the mental states that mediate the two. Only by encouraging innovation at the intersection of restoration, augmentation and intelligent systems can we realize this neurally-enhanced future.

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