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From Motor Control to Mental Regulation: Brain–Computer Interfaces in Emotion and Attention Modulation

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Abstract. Brain–computer interfaces (BCIs) were originally developed to restore or substitute motor functions by translating neural activity into external actions. With advances in neural signal processing, machine learning, and cognitive neuroscience, BCIs have increasingly extended beyond motor control toward the decoding and modulation of internal mental states, particularly emotion and attention. This paper reviews contemporary BCI-based approaches to emotion and attention regulation, drawing on evidence from electroencephalography-based neural decoding, neurofeedback training, and neuromodulation techniques. Using a structured literature review methodology, it examines how affective and attentional neural signals are identified, how feedback and stimulation systems influence these processes, and where the conceptual boundaries of mental-state modulation lie. The central question addressed is whether BCIs can move beyond influencing external behavior to shaping internal cognitive and emotional states and what technical, ethical, and philosophical constraints limit this transition. The analysis suggests that current BCI technologies can modulate emotional tendencies and attentional focus through learning and circuit-level intervention but do not enable deterministic control over consciousness. Instead, BCIs function as assistive and probabilistic modulatory tools within a highly adaptive and individually variable neural system.

Keywords: Brain–Computer Interface, Emotion Regulation, Attention Modulation, Neurofeedback, Neuromodulation

1. Introduction

Brain–computer interfaces (BCIs) establish a direct communication pathway between neural activity and external systems by decoding brain signals into control commands. While early BCI research primarily focused on motor control, recent developments in electroencephalography (EEG), machine learning, and cognitive neuroscience have shifted the focus of BCI research toward the modulation of internal mental states, such as emotion and attention, which are less directly observable but central to human cognition and behavior [1-3].

Within this emerging research landscape, two parallel lines of development are particularly relevant. First, EEG-based emotion recognition studies show that affective states correspond to identifiable neural patterns detected through signal-processing pipelines and deep learning models [1-3]. These findings challenge the view of emotion as purely subjective by demonstrating

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measurable neural signatures. Second, attention-oriented BCIs and neurofeedback systems have been applied to train individuals to regulate attentional focus, yielding improvements in visual and spatial attention in both healthy participants and clinical populations, including children with attention deficit/hyperactivity disorder [4-7]. Beyond decoding and training, neuromodulation techniques such as repetitive transcranial magnetic stimulation and deep brain stimulation provide additional evidence that targeted intervention in specific neural circuits can alter emotional and cognitive functioning by reshaping dysfunctional network dynamics [8-11].

Against this background, an important conceptual question arises: can BCIs move from controlling external behavior to modulating internal mental states such as emotion and attention, and if so, what are the limits of such modulation? This paper addresses this question through a structured literature review that integrates evidence from EEG-based decoding, neurofeedback training, and neuromodulation studies. By synthesizing findings across these domains, the paper aims to clarify the current capabilities and boundaries of BCIs in mental regulation, while also examining the ethical and philosophical implications of technologically intervening in human emotion and attention.

2. Foundations of BCIs and the neural correlates of emotion and attention

Brain-computer interfaces can be broadly categorized according to their architectural design and the functional operation. In terms of architectural design, BCIs are typically classified as either invasive or non-invasive. Invasive BCIs rely on implanted electrodes, such as those used in intracortical grids and electrocorticography, and offer high spatial and temporal resolution at the cost of neurosurgical intervention and potential long-term risks. Non-invasive BCIs, most commonly based on EEG, are safer and more practical for widespread use, although they are prone to noise and have low signal quality [1]. In terms of functional operation, BCIs may operate in open-loop or closed-loop systems. Open-loop systems decode neural signals without providing feedback to the user, while closed-loop systems incorporate real-time feedback or stimulation to influence ongoing neural activity. Closed-loop architectures are especially relevant for emotion and attention modulation, where the objective extends beyond passive decoding toward dynamic regulation of internal mental process. Although non-invasive EEG-based BCIs provide high temporal resolution, their limited spatial specificity poses a fundamental challenge for targeting the distributed neural networks underlying emotion and attention (Figure 1).

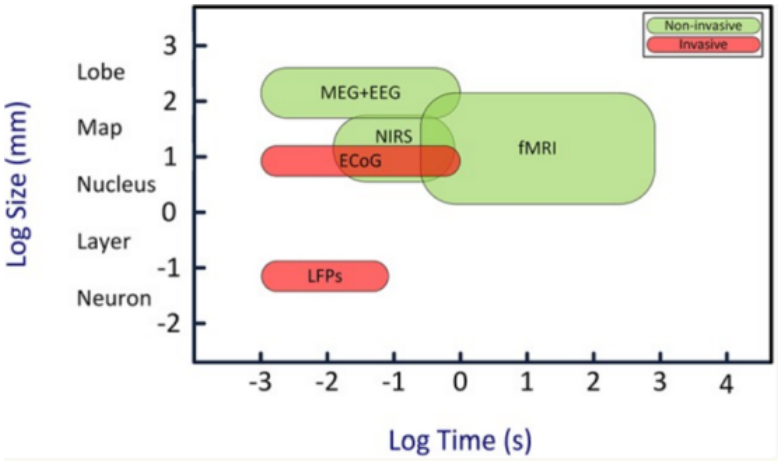

Figure 1. Trade-offs between spatial and temporal resolution across various BCI modalities [4]

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Emotion regulation is supported by brain circuits rather than localized areas, with fronto-limbic networks playing a central role. These networks are comprised of the frontopolar cortex, amygdala, and anterior cingulate cortex. EEG-based emotion recognition studies have demonstrated systematic associations between emotional states and the power of different frequency bands of brain oscillations, providing a physiological basis for decoding affective processes [1-3]. Conventional methods rely on feature engineering in the time and frequency domains, while recent studies utilizing deep learning aim at modeling the nonlinear dependencies between channels and timescales [12,13]. Crucially, these observations imply that emotional processes are neither purely subjective nor uniformly distributed across the brain; rather, they exhibit statistically identifiable patterns alongside substantial inter-individual variability. This trade-off between systematicity and variability is the key for the promise and challenge of BCIs targeting affective processes.

Attention, similar to emotion, is not localized to a single brain region but a product of relational interactions in large-scale networks. Cognitive neuroscience research has identified three major systems underlying attention control: the dorsal attention network, responsible for goal-directed and top-down attention; the ventral attention network, which mediates stimulus-driven reorienting; and the salience network, which prioritizes behaviorally relevant stimuli by integrating internal and external factors. Attention-oriented BCIs and neurofeedback systems can target these networks, especially when control of the attention is compromised.

The increasing focus on emotion and attention in BCI research reflects a broader paradigm shift from controlling peripheral physical actions of the body to manipulating the mental states of the user. Unlike motor behaviors, mental states are context-dependent, probabilistically defined, and shaped by experience and neuroplasticity. Therefore, BCIs targeting emotion and attention should not be conceptualized as deterministic control devices. Rather, they function as regulatory systems that influence cognitive and affective processes through the dynamic regulation of the neural networks.

3. BCI-based emotion recognition and regulation

Emotion-oriented BCIs rely on the detection of neurophysiological patterns associated with affective states. EEG remains the standard modality due to its high temporal resolution and portability compared to fMRI. The typical workflow—acquisition, artifact suppression, and feature extraction—is increasingly dominated by deep learning. These end-to-end architectures bypass manual feature engineering and improve classification accuracy, though they remain sensitive to experimental noise and high inter-subject variability.

The field is shifting from passive decoding to active modulation through closed-loop neurofeedback. These systems provide real-time neural feedback, allowing users to modulate signals linked to specific emotions. Most setups aim to reinforce patterns of emotional stability or dampen stress-related arousal. While data on anxiety management is promising, neurofeedback is a learned skill, not a passive treatment. Success depends on user agency and sustained practice, distinguishing it from invasive neuromodulation.

Widespread application is still limited by the fact that neural "signatures" are context-specific and vary significantly between individuals. Since emotion results from an interplay of biology, social context, and cognitive appraisal, neural data alone provide an incomplete picture. Current BCIs are better viewed as tools that "nudge" emotional reactivity rather than mechanisms for autonomous management. This gap necessitates personalized modeling and multimodal integration. For now, the valence-arousal model (Figure 2) remains the conventional framework for labeling and validation.

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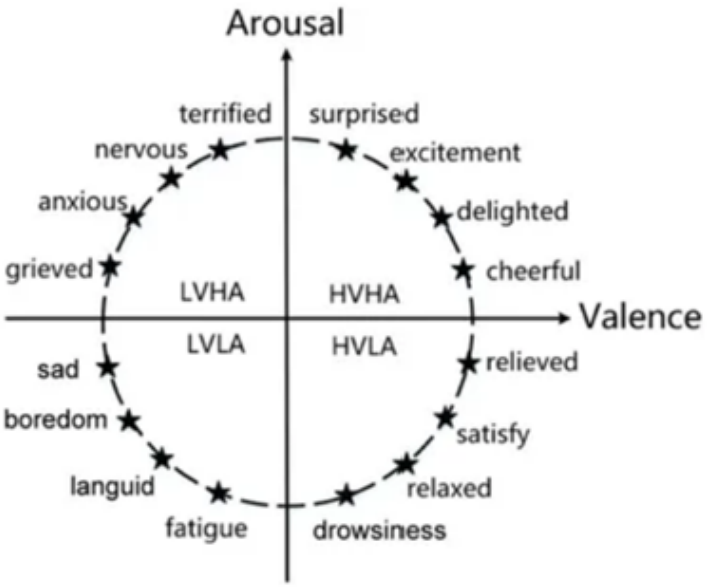

Figure 2. The emotion model of valence and arousal [1]

4. BCI and neurofeedback for attention modulation

Compared to emotion regulation, attention modulation has been regarded as a comparatively more achievable target for BCI-based interventions. This is partly due to the close relationship between attentional processes and task performance, as well as the behavioral and neural correlates that can be measured. Attention BCIs have typically relied on neurofeedback models in which users learn to regulate the neural correlates of sustained, selective, or spatial attention, as well as the attention they exhibit. EEG-based systems have often used event-related potentials or oscillatory activity as measures of attention for real-time training feedback [4, 5]. With sufficient interaction with the feedback, users learn to regulate their attention and, as a result, improve their performance on tasks. Most importantly, these systems do not automatically adjust users' attention; rather, they use learning and neuroplasticity to improve the users' control processes. As such, learning-based neurofeedback models represent the most salient non-intrusive approach for cognitive training and rehabilitation targeting attention.

Attention-oriented BCIs have been studied mostly in individuals with attention deficit/hyperactivity disorder (ADHD). BCIs have been integrated into training protocols not only for measuring attention behavior but also for large-scale reorganizations on brain networks. Studies in children with ADHD have shown that BCI-based neurofeedback can be used to retrain and normalize the functional topology of brain networks, leading to more efficient, coordinated patterns of neural communication [6]. Such changes on the network level suggest that BCIs focused on attention might offer more than superficial changes that are task-specific; they might, in fact, target and modify the neural correlates of attention. Furthermore, BCI-based attention training meta-analytic reviews suggest attention training via BCI helps reduce ADHD-related symptoms and also improves behavior [7]. Collectively, these findings reiterate the potential BCIs have for attention rehabilitation but also the need for more detailed attention and standardized measures of the outcomes. Attention training via BCI has been linked to the reorganization of large-scale brain networks, especially in the salience and attention networks. These networks also correlate with the changes in behavior (See Figure 3).

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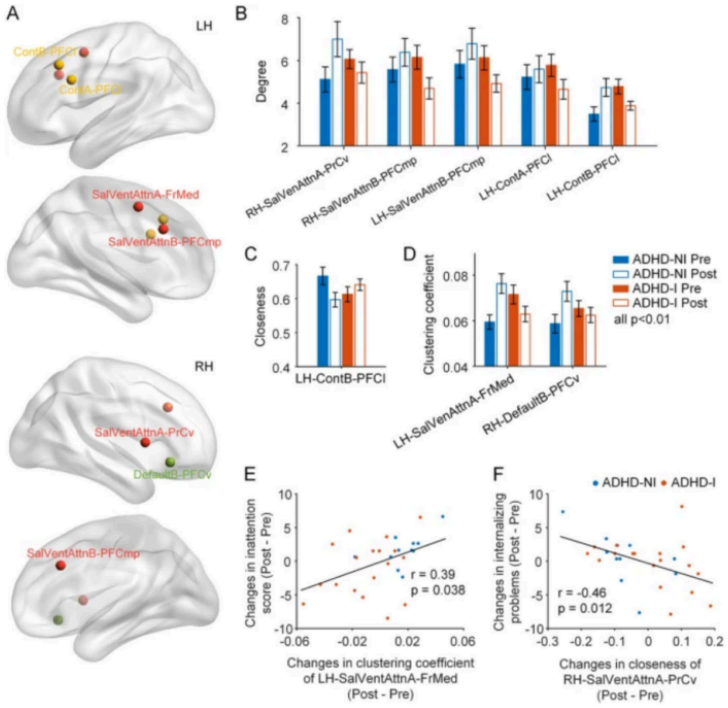

Figure 3. Brain network reorganization underlying behavioral improvemen following BCI-based intervention [6]

Recent developments in attention-modulating BCIs increasingly emphasize real-time closed-loop architectures that connect signal processing, feedback design, and user experience. Open-source platforms like ITACA make it easier to build and test such systems by offering modular frameworks for neurofeedback and BCI research [13]. The factors, including system latency, feedback mode, and task involvement, are of utmost importance in deciding the training efficiency and the user's willingness to comply. At a conceptual level, it remains essential to distinguish between the enhancement and the control of attention. Existing systems are mainly guiding the users to increase the ability to regulate attention through repetitive training and feedback, not directly through control over the cognitive processes. This difference in opinion fortifies the argument that the attention-oriented BCIs function by the means of the internal cognitive control capacity, which the user is allowed to keep while taking advantage of the brain's ability to adapt and learn.

5. Neuromodulation of emotion circuits: rTMS and DBS

Traditionally, BCI research operated on neural decoding and feedback-based learning, but studies of neuromodulation techniques like repetitive transcranial magnetic stimulation (rTMS) and deep brain stimulation (DBS) provided the recognition that neural circuits targeted by the intervention could be altered in terms of emotional and cognitive functioning. Whereas neurofeedback-based BCIs rely on user-driven self-regulation through learning, neuromodulation directly perturbs neural activity in certain brain areas or networks.

Among non-invasive neuromodulation techniques, rTMS has become one of the most widely used in clinical interventions, especially in the treatment of major depressive disorder, where it is often recommended for patients who do not respond to pharmacological treatment. Protocols for stimulation of the left dorsolateral prefrontal cortex have been found to reduce depressive symptoms, thereby implying prefrontal areas' involvement in regulating and integrating cognitive

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and emotional processes [8]. More recently, theta burst stimulation has emerged as a time-saving alternative to conventional rTMS, demonstrating the same therapeutic effects in selected clinical contexts while substantially reducing stimulation duration [9]. These findings further suggest that changing network-level dynamics can influence emotional states without requiring continuous or invasive intervention.

DBS represents a more invasive form of neuromodulation, offering increased precision through the placement of electrodes in particular subcortical targets. DBS has been successfully applied in treating resistant cases of obsessive-compulsive disorder and depression, whose targets are typically located in areas such as fronto-striatal and limbic circuits involved in the processing of emotions and cognitive control [10, 11, 14]. Clinical evidence indicates that the continuous activation of the affected areas can lead to alterations in the activity patterns associated with the illness, thereby permitting the reestablishment of a more adaptive network function. Most significantly, the impact of DBS is not limited to the site of stimulation but radiates through the brain, affecting the distributed neural circuits via connectomic pathways. This circuit-level perspective aligns with current views that emotion and attention arise from large-scale network interactions rather than isolated regional activity.

Conceptually, neuromodulation provides a critical link between decoding-based BCIs and more direct intervention strategies. While BCIs are mainly concerned with the mapping of the brain signal and giving feedback for learning. rTMS and DBS are proof that stimulation applied from the outside can change the way neurons act and facilitate their functioning better. This union prompts the development of systems that integrate real-time decoding of neurones with the adaptive one that controls the stimulation, making it possible to very accurately and personally modulate the two realms of emotion and attention. Such systems, however, also bring up significant moral and psychological issues. Direct intervention in neural activity prompts concerns regarding user autonomy, the authenticity of emotional experience, and the potential medicalization of normal emotional variability. These problems certainly highlight the importance of clearly distinguishing therapeutic intervention from cognitive or emotional enhancement and highlight the need for ethical frameworks that prioritize patient agency, informed consent, and long-term well-being.

6. Ethical, philosophical, and future reflections

As BCIs and neuromodulation technologies increasingly focus on internal mental states, ethical issues cannot help but become intertwined with their technological development and utilization. Perhaps the first issue is the distinction between influencing, modulating, and controlling emotions and attention. The existing BCI systems mainly rely on probabilistic modulation and learning mechanisms rather than deterministic control over the state of consciousness. Overemphasizing the ability of BCIs to control the mind could lead to a lack of understanding of the technological limitations and the intrinsic neural system complexities.

BCIs are also being considered for cognitive enhancement and attention training, aside from their utilization in treating various medical conditions. While this could potentially enhance attention and overall performance, there is also the possibility of issues involving autonomy, psychological effects, and the exacerbation of social inequalities. The enhancement-oriented utilization of BCIs could also lead to the promotion of a narrow definition of the best state of mind and the creation of a new type of performance anxiety.

The development of BCIs in the future must focus on issues involving user agency, personalization, and ethical transparency. Adaptive BCI systems that respect individual differences

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and allow meaningful user choice will be essential for ensuring that advances in neural technology remain socially responsible and beneficial.

7. Conclusion

The studies reviewed in this paper highlight a definite trend of the trajectory of brain–computer interface research. Though early BCIs were first conceived as adaptive therapies that provided externalized neural instructions to regain motor capabilities, more recently, the role of internal mental states, emotion, or attention in how these systems might interact with them has become an area of increasing investigation. Evidence from EEG-based decoding, neurofeedback training, and neuromodulation techniques taken together demonstrate that affective and attentional processes interact with measurable neural dynamics that can be partially modulated by feedback, learning, and circuit-level intervention. At the same time, these results illustrate critical conceptual and technical limitations. Emotional and attentional processes are derived from highly adaptive neural systems formed by individual differences, learning history, and environmental context. Consequently, BCI interventions seldom yield deterministic results. Even more direct types of neural intervention, such as repetitive transcranial magnetic stimulation or deep brain stimulation, tend to change the likelihood of a specific neural state, as opposed to establishing precise effects on emotion or cognition. In that sense, BCIs should not be thought of as "technologies that control the brain directly." Instead, they act as interfaces with cognitions and facilitate mechanisms of neural self-regulation. This view has important implications for the subsequent development of BCI technologies. Rather than universal models of how we should predict and control mental states (in a uniform way), from now on more personalized processing approaches in which signals are interchanging both cognitively and psychically and situated with behavior. Recognizing both the potential as well as the limits of existing technology, BCIs can be placed much more realistically as aids in cognitive training, neurorehabilitation, and emotion regulation. Their long-term usefulness will depend not only on improved decoding accuracy or system design but also on continuing to maintain a human-centered perspective that respects the complexity and variability of human mental life.

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