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EEG at the Edge: Signals, Selves, and Systems

Marco Cursi, BME[1,*], Anna Bellini, MD[1], Massimo Filippi, MD[2]

[1]Clinical Neurophysiology Unit, Department of Neurology, IRCCS San Raffaele Scientific Institute, Via Olgettina, 60 - 20132 Milan, Italy

[2]Neurology, Neurorehabilitation, and Clinical Neurophysiology Units, Department of Neurology; Neuroimaging Research Unit, Division of Neuroscience; IRCCS San Raffaele Scientific Institute; Vita-Salute San Raffaele University, Via Olgettina, 60, 20132 Milan, Italy

*Correspondence should be addressed to Marco Cursi, cursi.marco@hsr.it

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Abstract

Electroencephalography (EEG) is undergoing a profound transformation, from a passive diagnostic tool to an active interface for communication, intervention, and neuroadaptive control. This commentary explores the current state and future trajectories of EEG-based technologies, focusing on emerging paradigms that redefine the role of the brain within technological and therapeutic environments.

We begin by examining the digital present: while EEG systems are now more portable, connected, and computationally empowered than ever before, technical limitations and interpretive bottlenecks persist. We then trace the rise of closed-loop neuromodulation, with clinical evidence supporting personalized, responsive stimulation in epilepsy and Parkinson's disease. In parallel, multimodal EEG, particularly EEG-fMRI and EEG-fNIRS integration, is offering unprecedented insights into spatiotemporal brain dynamics, cognitive biomarkers, and neurovascular coupling.

The development of brain-computer interfaces (BCIs) further illustrates EEG's shift from monitoring to action, as neural signals become control inputs for communication, rehabilitation, and assistive technologies. Recent innovations in AI and machine learning are accelerating this trend, enabling real-time decoding, anomaly detection, and adaptive user-specific pipelines. At the frontier of this evolution lie brain-to-brain interfaces (B2BIs), experimental systems that challenge notions of agency, responsibility, and cognitive sovereignty by enabling direct neural communication between individuals.

Across these domains, a central theme emerges: innovation must be accompanied by reflection. We argue that EEG is no longer just a measure of brain activity; it is becoming a medium of agency, and with it, a mirror for our evolving relationship with technology, autonomy, and selfhood. Building that future demands not only technical precision, but also ethical foresight and interdisciplinary collaboration.

Keywords: Electroencephalography (EEG), Digital neurotechnology, Closed-loop neuromodulation, Multimodal brain monitoring, Brain–computer interface (BCI), Artificial intelligence, Machine learning, Brain-to-brain communication, Neuro ethics, Cognitive sovereignty

Introduction: EEG at the Edge

The evolution of electroencephalography (EEG) reflects the broader trajectory of neuroscience itself: from analog traces of alpha waves to today's cloud-integrated, AI-enhanced signal architectures. In our recent work [1], we traced this development through historical and conceptual milestones, positioning EEG as both a reflection of brain function and a catalyst for emerging neurotechnological paradigms. Yet the trajectory is far from linear. Innovations such as wearable EEG, digital biomarkers, brain-computer interfaces, and brain-to-brain communication [2] are not just refinements of earlier models, they signal a qualitative change. EEG is no longer confined to clinical diagnostics or laboratory research. It is migrating toward real-time, adaptive applications in rehabilitation, consumer neurotech, and behavioral modulation [3]. The brain is no longer treated as a closed system, but increasingly approached as a dynamic, responsive node within larger technological and social networks.

In this commentary, we reflect on this transitional moment: a threshold where EEG moves beyond signal acquisition to become a medium of agency, mediation, and even transformation. What are the implications of connecting minds to machines, and, perhaps, to each other? How do we safeguard autonomy, intention, and identity in a landscape where cognition itself may be distributed? EEG is no longer merely a tool of measurement. It is a mirror, and what it reflects depends not only on how we build, but also on how we choose to see.

The Digital Present: Unlocking Potential, Confronting Limitations

Over the past three decades, electroencephalography has undergone a profound digital transformation. What began as simple signal digitization has evolved into a sophisticated ecosystem enabling multimodal integration, cloud-based analytics, and high-throughput data acquisition. Modern EEG systems combine high-resolution, artifact-resistant amplifiers with modular architectures designed for integration across clinical and research settings. On the software side, a wide array of analytical tools - some already implemented in commercial platforms, others emerging from recent research - enable advanced signal processing These include preprocessing workflows [4], ICA decomposition [5], non-linear feature extraction, such as entropy or fractal dimension [6,7], coherence and connectivity analysis [8], and source localization [9]. Although some of these techniques are not yet widely implemented in commercial systems, they represent promising directions for the future of advanced EEG analysis. Together, these advances are reshaping both clinical workflows and experimental protocols in cognitive neuroscience.

Recent applications reflect this shift. EEG now supports real-time monitoring of mental workload in high-stakes environments [10], decoding of affective states [11], and neurofeedback for conditions such as attention deficit hyperactivity disorder (ADHD) and anxiety [12].

Ambulatory platforms allow for continuous epilepsy monitoring [13], frequently complemented by video-EEG, which remains a cornerstone in cases where the temporal correlation between electrical activity and behavioral manifestations is crucial for accurate diagnosis, particularly when standard EEG alone proves inconclusive [14]. These platforms are increasingly used in sleep diagnostics, and cognitive profiling in aging populations [15].

In parallel, the rise of wearable and consumer-grade EEG has catalyzed research outside the lab, powering studies in neuromarketing [16], adaptive learning [17], and real-world neuroergonomics [18].

Yet limitations persist. Signal quality in mobile configurations remains susceptible to motion artifacts and environmental noise. The sheer scale of EEG data often exceeds our ability to extract clinically actionable insights, particularly in longitudinal contexts. A lack of harmonized acquisition protocols and the proliferation of proprietary formats hamper interoperability and reproducibility. Moreover, while commercial systems increasingly promote plug-and-play simplicity, routine clinical deployment still faces with calibration demands, technician variability, and interpretive bottlenecks.

What emerges is a paradox: EEG has never been more powerful, yet it is rarely frictionless. Moving forward requires more than smarter hardware or advanced analytics. It demands a conceptual shift: from collecting ever-larger datasets to deriving ecologically valid, interpretable, and clinically meaningful insights. EEG must not only evolve technically; it must become functionally responsive to the contexts and decisions that define patient care.

Closed-Loop EEG Systems: When the Brain Talks Back

If digital EEG platforms have taught us to listen to the brain, closed-loop systems challenge us to speak back. What happens when the EEG signal does not end in a database, but triggers an action, autonomously, and in real time? The traditional role of EEG as a passive monitoring tool is being redefined by the emergence of closed-loop systems, neurotechnologies capable of detecting specific brain activity patterns in real time and delivering targeted stimulation in response. These systems represent a shift from observation to interaction, enabling the brain not only to be read, but also to be modulated dynamically.

One of the most established clinical examples is the NeuroPace RNS® (Responsive Neurostimulation) System for drug-resistant focal epilepsy. Unlike open-loop devices that deliver stimulation at fixed intervals, RNS continuously monitors intracranial EEG and administers electrical pulses in response to detected seizure-like activity. Recent evidence shows that, beyond seizure suppression, RNS may also preserve or improve cognitive outcomes and mood, especially when the epileptogenic focus is on the left temporal lobe [19]. However, seizure patterns often evolve unpredictably over time, occasionally bypassing preset detection thresholds. These dynamics highlight the need for adaptive algorithms and AI-assisted reprogramming [20]. In parallel, machine learning techniques such as vision transformers are being explored to distinguish physiological ripples from pathological discharges in iEEG, enhancing accuracy and specificity [21].

In Parkinson's disease, closed-loop adaptive deep brain stimulation (aDBS) is rapidly gaining traction. These systems modulate stimulation based on oscillatory biomarkers like betaband and finely tuned gamma activity. A multicenter study by Li and colleagues [22] found that aDBS targeting subthalamic beta bursts significantly improved motor outcomes and reduced reliance on medication. Gamma oscillations have emerged as reliable biomarkers for tracking medication cycles in naturalistic settings [23], and the feasibility of in-home adaptive stimulation has been demonstrated using the RC+S platform [24]. Additional evidence reinforces the potential of rhythm-responsive neuromodulation to alleviate symptoms such as freezing of gait [25,26]. Collectively, this growing body of research points toward a shift to intelligent, personalized DBS systems that adapt to patients' neurophysiological states in real time.

Emerging applications extend to neuropsychiatric conditions as well. Experimental systems coupling EEG with non-invasive modalities like transcranial alternating current stimulation (tACS) or focused ultrasound are being tested for depression, obsessive compulsive disorder, and cognitive decline, responsive to both brain state and behavioral context [27,28].

Yet the promise of closed-loop systems brings new complexity: algorithmic latency, inter-individual variability, and ethical concerns related to autonomy and unintended modulation. Still, these challenges may signal a new therapeutic frontier, where the brain not only expresses dysfunction, but actively participates in its own restoration.

Multimodal EEG: When One Modality isn't Enough

EEG offers unmatched temporal resolution, but its spatial limitations have long constrained its interpretability. To address this, researchers increasingly turn to multimodal integration — particularly with functional MRI (fMRI) and near-infrared spectroscopy (fNIRS), to combine fast electrophysiological dynamics with the spatial precision of hemodynamic signals. These hybrid paradigms allow for a richer, more layered understanding of brain activity.

In cognitive neuroscience and clinical neurology, EEG-fMRI has become a powerful tool. Simultaneous recordings enable researchers to align EEG events, such as epileptic spikes or task-related potentials with BOLD signals, enhancing both spatial and temporal resolution. Beyond classical applications in resting-state analysis, emotion regulation, and seizure localization, recent studies highlight the expanding utility of EEG-fMRI integration. Dynamic EEG spectral power has been shown to correlate with evolving fMRI network topologies during rest [29], and links between alpha/beta rhythms and BOLD activity have been observed in affective and motor domains, including depression and motor imagery tasks [30]. In parallel, EEG-fNIRS offers a portable and cost-effective alternative better suited for real-world applications. This dual-modality setup enables neurovascular coupling analysis in naturalistic settings, such as neurorehabilitation, pediatric research, and bedside monitoring [31]. It has shown promise in conditions like ADHD, stroke, and infantile epilepsy, offering insights where MRI is impractical or inaccessible.

As EEG becomes increasingly wearable and cloud-enabled, multimodal integration is poised to become the new standard, not only in research, but in diagnostics, neurofeedback, and personalized BCI design. In this context, EEG no longer serves merely as a standalone signal: it becomes a convergence point for neural data streams, contextual information, and adaptive control, expanding the horizon of what brain monitoring and modulation can achieve.

Brain-Computer Interfaces: From Promise to Practice: At What Cost?

As EEG systems become more accurate and integrated with other modalities, a new horizon emerges: using brain activity not just to reflect, but to act. Brain-computer interfaces (BCIs) transform neural signals into actionable commands, enabling users to control external devices by intention alone. Over the past decade, EEG-based BCIs have progressed from experimental systems to practical tools for motor rehabilitation, assistive communication, and cognitive enhancement.

Users can now navigate spelling interfaces using P300 responses [32,33], operate devices through motor imagery [34,35], or control external systems via steady-state visual evoked potentials [36]. These paradigms underpin a growing range of clinical applications, including communication support in locked-in syndrome, post-stroke neurorehabilitation, and mobility enhancement through smart wheelchairs and exoskeletons [37].

Yet translating these capabilities into everyday settings remains difficult. Real-time BCI use often demands lengthy calibration, stable signal acquisition, and intense concentration, factors that challenge long-term usability. Inter-subject variability further limits generalizability, requiring frequent manual tuning. Many users experience cognitive overload when modulating brain rhythms, and 15–30% fail to achieve effective control altogether, a phenomenon known as "BCI illiteracy" [38].

Recent research points toward a more adaptive and emotionally responsive BCI landscape. Current research offers a comprehensive overview of existing EEG systems and their limitations [39], alongside streamlined decoding pipelines that improve classification accuracy while minimizing computational demands [17,40]. In the affective domain, transformer-based models such as the Multi-Brain Regions Spatiotemporal Collaboration transformer (MBRSTC former) have been proposed for EEG-driven emotion recognition [41], while other work emphasizes the critical role of interpretability and cross-cultural generalizability in model design [42]. Since non-stationarities arising from mental state fluctuations or device-related factors can impair BCI performance, adaptive systems capable of real-time adjustment have been proposed. These include paradigms that integrate error-related potentials into reinforcement learning loops to optimize control [43], as well as dual-mode systems combining SSVEP and P300 signals to enhance performance and reliability [44]. These trends reveal a field moving beyond monolithic signal interpretation toward multi-modal, adaptive, and user-centered architectures. EEG is increasingly used alongside EMG, EOG, and eye-tracking to reduce cognitive load and improve resilience [45,46]. Simultaneously, AI-driven meta-classifiers and context-aware protocols are being developed to detect shifts in attention, fatigue, or engagement, dynamically adjusting system behavior [47].

The question is no longer whether BCIs can function, but for whom, and under what conditions, they can truly empower. Balancing performance with usability, personalization with scalability, and innovation with ethical foresight remains the defining challenge of this next generation of neural interfaces.

AI and Machine Learning: From Signal to Insight

Raw control is nothing without intelligent interpretation. As EEG systems generate ever-larger and more complex datasets — through long-term monitoring, wearable platforms, and brain-computer interfaces — the need for automated, scalable, and adaptive analysis becomes critical. This is where artificial intelligence (AI) and machine learning (ML) are reshaping the neurotechnology landscape, not to replace clinicians, but to amplify their interpretive power [48].

Traditional EEG analysis relies on expert-driven feature extraction and visual inspection, which are time-consuming and susceptible to inter-rater variability. In contrast, ML algorithms can detect patterns in raw or minimally preprocessed EEG, enabling tasks such as seizure detection, sleep stage classification, cognitive and affective state decoding, and real-time BCI signal interpretation [49,50]. Especially in high-pressure environments, like the ICU or neonatal monitoring, automated anomaly detection can reduce time to diagnosis and increase clinical responsiveness.

Recent studies have demonstrated that deep learning architectures, including convolutional and recurrent neural networks, often outperform traditional classifiers in detecting epileptiform discharges and estimating mental workload [50]. Hybrid pipelines are also emerging: the SCORE-AI system, for example, combines feature engineering with deep models and has shown expert-level performance in multicenter validations [48]. These tools are beginning to find their place in routine workflows, functioning as decision-support systems in clinical EEG reading.

In BCIs, AI unlocks adaptability. Classifiers that evolve in response to user-specific dynamics, like fatigue, drift, or attentional shifts, are key to overcoming “BCI illiteracy” and enabling personalized decoding [51]. Reinforcement learning and meta-classification are being employed to tune system responses in real time, improving usability and long-term engagement [52].

However, this progress comes with new questions. How do we ensure transparency in deep models operating on sensitive neurodata? What are the ethical implications of algorithmic recommendations in diagnosis or therapy? And how do we validate these systems across populations, pathologies, and recording conditions?

As EEG moves toward real-time, high-volume, and user-centered applications, AI is no longer a mere add-on. It is becoming a co-pilot in the journey from signal to insight — helping us not just to process more data, but to ask better questions of the brain.

Brain-to-Brain Interfaces: Interfaces or Interferences?

At the intersection of algorithms and agency lies a radical threshold: not just brain-machine, but brain-to-brain communication. While BCIs have matured into viable clinical tools, brain-to-brain interfaces (B2BIs) remain at the speculative frontier, provocative, experimental, and ethically charged. These systems aim to transmit information directly between two brains, coupling EEG-based decoding in a “Sender” with neurostimulation, via transcranial magnetic stimulation (TMS), tACS, or focused ultrasound, in a “Receiver” [53].

Early human studies have demonstrated binary communication using non-invasive B2BIs, including paradigms where a participant mentally triggers a “fire” command that is transmitted across the internet and executed through TMS-induced motor activation in another individual [54]. However, this form of stimulation appears to have faded from current research efforts, with no studies published after 2021 replicating or extending such paradigms. A recent review confirms this trend, noting the absence of post-2021 experimental replications and highlighting a shift in focus toward alternative B2BI architectures [55]. Other experiments have used SSVEP-based encoding to coordinate cooperative tasks, including collaborative paradigms such as multi-user interfaces and brain-to-brain interaction systems [56]. While still rudimentary, these approaches demonstrate the technical feasibility of direct neural influence.

Beyond the lab, B2BI is being explored in conceptual frameworks for neurorehabilitation, such as the use of synchronized tACS to enhance neural entrainment between therapist and patient, potentially amplifying recovery through interpersonal synchrony [57]. Though largely theoretical, these ideas reflect a growing interest in inter-brain dynamics as a therapeutic axis.

Yet as B2BI shifts from "reading" to "influencing" another mind, it blurs foundational ethical boundaries: Where does my intention end and yours begin? If a motor action is induced by an external brain signal, who is responsible, the sender, the receiver, or both? These dilemmas become sharper in multi-agent systems and clinical or military contexts [58].

Additional concerns arise around neural privacy. Sharing brain signals may inadvertently expose emotional states, intentions, or diagnoses, raising the specter of neurohacking, manipulation, or psychological overreach. As Elisabeth Hildt notes, "B2BIs are not only instruments of communication, but also instruments of co-agency" [59]. This notion has recently been echoed and expanded in the context of neurotechnology ethics, where co-agency is reframed as relational agency between users and devices, highlighting the shared nature of autonomy and identity in technologically mediated cognition [60].

To responsibly explore B2BI, ethics must run in lockstep with engineering. We need protocols for meaningful consent that extend beyond procedural checklists. We must ensure that receivers can distinguish internal thoughts from externally induced states and that architectures remain transparent and auditable. Above all, we must affirm the sanctity of cognitive sovereignty, the right to control not only what we express, but what we absorb [61]. This imperative becomes even more urgent as research moves toward large-scale brain-computer constellations, where identity, autonomy, and accountability may be distributed across networks of minds. Recent proposals for decentralized cognitive architectures, such as 'Mind plexes' and 'Cloud minds', raise profound questions about how privacy, responsibility, and agency can be preserved in collective systems [62]. We may soon be able to transmit thoughts. The deeper question is: Are we ready to share responsibility for them?

Conclusion: Vision Demands Responsibility

Electroencephalography (EEG) remains one of the most widely used tools for diagnosing and monitoring neurological disorders, including epilepsy, sleep disturbances, encephalopathies, and altered states of consciousness. Its ability to provide real-time insight into the brain's electrical activity makes it an essential instrument for clinical practice and research. However, EEG is no longer confined to capturing brain activity, it is evolving into a dynamic interface through which we communicate, adapt, and act.

As EEG systems evolve into multimodal, adaptive, and cloud-connected infrastructures, they move from instruments to architectures. From digital EEG platforms and closed-loop systems to BCIs and experimental brain-to-brain interfaces, the technological curve is steep and accelerating. Innovations once unthinkable are now accessible, often freely, while others remain secluded in experimental labs or restricted domains.

But as neurotechnologies extend their reach, the notion of the individual itself begins to shift. In a future where brains are networked with machines, and perhaps even with other minds, where is the boundary of self? Do our thoughts remain ours, or are they co-authored by systems we cannot fully perceive? Are our actions truly autonomous, or subtly shaped by predictive systems that anticipate and nudge behavior? These are no longer questions for science fiction, but emerging realities in military research, assistive technologies, and consumer neurotech. As interfaces evolve from tools to infrastructures, we risk dissolving the individual into a larger system, technologically powerful, but ethically opaque. And here a deeper uncertainty emerges: who controls the system? Who sets the thresholds, tunes the models, governs the flow of neural information across platforms and protocols? In a hybrid brain-machine network, actions are no longer just a matter of personal autonomy, they become a question of control.

Preserving human agency means more than enabling choice; it means protecting the very space where choices are possible.

The future of EEG requires not only technical innovation but also philosophical clarity. Because as we build systems that listen to the brain and speak back, the ultimate question becomes: what kind of selves are we designing for, and what kind of world are we wiring them into?

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