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Brain-Computer Interface

Bridging Technology, Education, and Ethics

*Edited by Ricardo A. Ramirez-Mendoza,
Jose Alejandro Aybar M. and Ruben Morales-Menendez*



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Morales-Menendez*

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Artificial Intelligence (AI) is a rapidly developing multidisciplinary research area that aims to solve increasingly complex problems. In today's highly integrated world, AI promises to become a robust and powerful means for obtaining solutions to previously unsolvable problems. This Series is intended for researchers and students alike interested in this fascinating field and its many applications.

Meet the Series Editor



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Preface

The convergence of disciplines, such as cognitive science with engineering, medicine, education, mobility technologies, artificial intelligence, and others, is redefining how we approach complexity across various application sectors. This edited volume, *Brain-Computer Interface - Bridging Technology, Education, and Ethics*, aims to provide a broad and comprehensive study that includes theoretical support as well as a practical approach with case studies and reports of experimental results, allowing the reader to appreciate and understand the potential of Brain-Computer Interfaces (BCIs) and other neurotechnologies. By synthesizing insights from leading experts across various disciplines, this book illuminates the profound ethical, clinical, and industrial implications of neurotechnological integration, offering a vital roadmap for understanding the tools that will shape the future of human interaction, health and rehabilitation, education (STEM learning), ethics, and disruptive topics such as democratic governance, neuro-rights, and cognitive dignity.

This book includes 7 chapters organized as follows. Chapter 1 presents a systematic review of the state of the art in the application of electroencephalography (EEG)-based BCIs in Science, Technology, Engineering, and Mathematics (STEM) education. The results of this study highlight four important dimensions of knowledge: (1) Attention and engagement monitoring, (2) Neurofeedback for inclusion and special education, (3) Robotics and engineering practice, and (4) Emotion recognition and affective learning. The prospects for applying these technologies to STEM education are promising, with the potential to improve education through meaningful teaching and learning experiences. Because of the ability to obtain real-time neurological signals, learning metrics can be derived that relate to student engagement in their own learning, student attention, motivational aspects, applications to adaptive learning for diverse learning styles, and personalized teaching, leading to a more inclusive education. There is significant research and experimental studies with important contributions in this area.

The BCIs from the perspectives of democratic governance, neuro-rights, and cognitive dignity are addressed in Chapter 2. This Chapter 2 establishes a roadmap for creating research and prototyping laboratories that prioritize metrics of effectiveness, safety, and equity, aligned with Sustainable Development Goals (SDG) 5 and 10, among others. This work seeks to answer the political questions surrounding these technologies, considering what types or classes of neurotechnology should be promoted in the Global South and to whom they should be directed, bearing in mind that BCIs reproduce hierarchies, exploitation, and dependency. Indeed, the Global South presents an opportunity to build governance for the data generated by BCIs within the context of human well-being. An ethical and responsible framework for the use of this data, as well as a governance framework, must be developed. It is emphasized that the social, political, and academic ecosystems must be involved in these developments, as they are interconnected entities.

Chapter 3 shows how BCIs turn that promise into practice by making three essentials: Cognitive Readiness (planning and flexibility), Situational Awareness (perceiving what matters), and Motivation/Willpower (sustained effort), measurable, coachable, and coordinated in real time. This chapter introduces a vendor-agnostic, closed-loop “anticipate → cue → lockout → learn” policy that forecasts near-term lapse risk, delivers a single well-timed micro-intervention, and then audits what it prevented (e.g., prevented-lapse rate, lead-time, intervention yield). The potential applications include flight and mission, surgical training, rehabilitation, athletics, and high-stakes decision-making, each using the same control logic with domain-specific tuning. The authors close with evaluation designs and clear ethical guardrails (privacy, transparency, equity). The result is a practical playbook for researchers, educators, clinicians, and operators who need resilient, auditable gains, when performance under pressure really matters.

One of the most relevant aspects highlighted in neural technologies is their enormous capacity to detect interaction with the environment by interpreting brain signals. In Chapter 4, EEG technology enables the activation of neuromuscular systems using external actuators and equipment, for example, for rehabilitation purposes. This allows for the creation of closed control loops that enable sensing, that is, obtaining signals using EEG technology, processing the information, interpreting it, and generating control actions that connect to external devices, such as actuators, motors, and mechanical equipment that stimulate neuromuscular activity. The authors extend the concept of BCI (signal acquisition, preprocessing, feature extraction, pattern classification, and control output) to motor rehabilitation applications for stroke patients. The results demonstrate rehabilitation and recovery of basic functions, including upper limb and walking. Additionally, the chapter proposes topics for future research and offers recommendations on technological and clinical challenges.

Chapter 5 presents an application of AI-driven digital twins (DTs) to the healthcare domain, particularly in diagnosis. It is well known that neurodegenerative diseases are complex to treat, and many challenges currently exist in finding medical solutions that can improve, halt, or slow the degenerative effects of this debilitating disease. The authors propose using technologies based on the concept of “deep learnability.” This concept can be efficiently modeled given biological constraints and data limitations. This work also advocates for a mandatory three-tier framework for any AI-driven digital twins: (1) technical validation ensuring computational robustness; (2) biological validation confirming alignment with established biomarker and imaging data; and (3) clinical validation demonstrating tangible utility in improving patient diagnosis and outcomes. This structured approach, combined with a call for global standardization and ethical design, is essential to translate the promise of DTs into clinically viable tools.

The spectrum of applications for technologies that use human physiological signals, including those originating in the brain, is broad. Chapter 6 discusses one of the most outstanding applications for road safety. The convergence of multiple disciplines, such as neuroscience, with technology yields surprising results, and the application opportunities are limitless. Ultimately, the goal is for advances in science and technology to improve human life and extend people’s capabilities in fields such as

road safety. This chapter of the book explores three lines of research. First, it presents the application of Advanced Driver Monitoring for Assistance Systems (ADMAS) to automotive safety. In ADMAS, the driver's physiological signals are processed to prevent and mitigate accidents by detecting driver fatigue and distraction. Besides, the chapter addresses Ambient Assisted Living (AAL) through the lens of Emotional Domotics (ED), proposing responsive environments that dynamically adapt to the user's affective state in real time to maximize psychological well-being. The integration of the BCIs will allow the vehicle to optimize its interaction with the driver and to apply emergency measures when needed. Furthermore, this chapter presents how neural technologies are integrated into an Ambient Assisted Living (AAL) context through the lens of ED, proposing responsive environments that dynamically adapt to the user's affective state in real time to maximize psychological well-being.

Finally, Chapter 7 addresses the applications of BCIs in security and defense strategies. In this context, the authors describe the concept of the "enhanced soldier". An "enhanced soldier" requires a comprehensive training and development plan; precisely, the focus of this chapter is to provide a technical and scientific discussion of the technological aspects of neurotechnology applied to the military, and it also includes an interesting debate on the moral, legal, and social consequences of implementing neurotechnology in a military context. This research concludes by recognizing the applicability and potential of BCIs to save lives and to preserve individual autonomy, dignity, and human rights. To achieve this, strategic collaboration between medical professionals, engineers, lawyers, the military, and ethicists is required, as well as international dialogue to develop unified standards.

The completion of this volume would not have been possible without the invaluable contributions and steadfast support of numerous individuals. We wish to express our sincere gratitude to José Alejandro Aybar M. and Ruben Morales-Menendez for being part of the editorial committee whose rigorous feedback and scholarly insights significantly enhanced the quality of this work. Special thanks are also due to Prof. Julian C. Pena-Bermudez for their logistical and technical assistance throughout the publication process. Finally, I extend my most profound appreciation to all the contributing authors for sharing their expertise and for their commitment to advancing the field of neurotechnology.

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Brain–Computer Interfaces (BCIs) in STEM Learning

Sandra Cano

Abstract

Brain–computer interfaces (BCIs) are emerging technologies that enable direct communication between the human brain and external devices. As BCIs transition from laboratory research to educational practice, they offer new possibilities for advancing STEM learning. This study presents a systematic literature review of research on electroencephalography (EEG)-based BCIs applied in educational contexts, following the PRISMA 2020 methodology. A total of 683 records were identified from Scopus and Web of Science, resulting in a final selection of 29 empirical and conceptual studies published between 2020 and 2025. The analysis reveals that BCI applications in education concentrate on four primary domains: (1) attention and engagement monitoring, (2) neurofeedback for inclusion and special education, (3) robotics and engineering practice, and (4) emotion recognition and affective learning. Across these domains, the most frequently explored processes are attention, engagement, motivation, and memory, with consumer EEG devices such as Muse, Emotiv, and NeuroSky enabling real-time monitoring of students' cognitive states. Studies also integrated machine learning and affective computing to classify emotional states and deliver adaptive feedback in real time. Despite current limitations such as signal quality, electrode calibration, and ethical concerns, the findings suggest that EEG-based BCIs have strong potential to foster personalized, inclusive, and interdisciplinary STEM education, positioning them as transformative technology for future neuroadaptive learning environments.

Keywords: STEM learning, EEG, Educational robotics, brain-computer interfaces (BCIs), educational technology

1. Introduction

Learning is the cognitive process of acquiring knowledge and skills through education [1]. Therefore, the purpose of education is to provide students with cognitive skills related to problem-solving, logical, and creative thinking. Cognitive abilities are of interest to researchers in neuroscience, integrating the concept of educational neuroscience (or neuroeducation) as an interdisciplinary field of study that seeks to implement knowledge about the neural mechanisms of learning into educational practice and to understand the impact of the learning process on the student's brain [2].

The integration of neuroscience and education has given rise to innovative technologies that expand the possibilities for teaching and learning in science, technology, engineering, and mathematics (STEM). Among these, electroencephalography (EEG)-based brain-computer interfaces (BCIs) represent a frontier technology capable of translating neural signals into commands for external devices [3]. Initially designed for clinical and rehabilitation purposes, BCIs are now entering classrooms and laboratories, offering opportunities for hands-on experimentation, adaptive learning environments [4], and inclusive educational practices. Their presence in STEM education is timely [5], as they align with the global push toward developing twenty-first-century skills such as problem-solving, critical thinking, and computational literacy. Therefore, BCIs can be relevant to understanding how students learn most effectively [6].

EEG allows real-time monitoring of neural activity by capturing voltage fluctuations across different frequency bands. This capability makes it possible to detect cognitive states such as attention, engagement, and mental workload. In STEM learning environments, this capability has two main implications. First, EEG-based BCIs can be employed as pedagogical tools, enabling students to explore the intersection of neuroscience, engineering, and computer science through interactive projects – for example, controlling robots, visualizing their own brain signals, or programming adaptive interfaces. Second, they can serve as supportive technologies, providing feedback to educators and learning systems on students' cognitive states, thereby allowing more personalized instruction [7] and potentially reducing barriers for learners with diverse needs [8].

EEG-based BCIs can also serve as an alternative for measuring and evaluating student memory [9], cognitive skills [10], learning styles [11], and attention [12]. This is particularly relevant given that many teachers often report difficulties in keeping students attentive and focused during the learning process. In classroom settings, it is common for some students to become distracted, lose interest, fall asleep, or engage in unrelated activities. EEG-based BCIs offer a complementary approach by providing real-time, objective indicators of students' cognitive states [13].

In addition, several studies have integrated EEG-BCIs with affective computing as an alternative approach to understand and support students' emotional states in STEM education [14]. Affective computing [15] focuses on the recognition, interpretation, and simulation of human emotions through technology. When combined with EEG, it becomes possible to detect patterns in neural activity that reflect affective dimensions such as motivation, stress, or frustration during learning tasks [16]. Furthermore, recent advances in machine learning [17] and deep learning [18] have been increasingly applied to EEG feature extraction and the classification of emotional data, enhancing the accuracy and responsiveness of affective BCI systems.

To conclude, this chapter aims to review the fundamental concepts of EEG-based BCIs, with a particular emphasis on their affective and educational dimensions, and to discuss their potential as transformative tools for STEM learning. By synthesizing current research, we highlight how BCIs can foster motivation, engagement, and inclusivity in STEM education, while also identifying challenges that must be addressed for broader adoption. The chapter is structured as follows: Section 2 presents the background and state-of-the-art on EEG-based BCIs and their connection to STEM and affective computing; Section 3 describes the methodological approach used in conducting the review; Section 4 reports the main findings and categorizes existing applications; Section 5 offers a critical discussion of

implications, limitations, and challenges; and finally, Section 6 concludes with recommendations and future directions for integrating BCIs into STEM learning environments.

2. Background and state-of-the-art

2.1 Affective BCIs

Affective brain-computer interfaces (affective BCIs) combine traditional BCI technologies with the principles of affective computing to monitor, interpret, and respond to users' emotional states [19]. Unlike conventional BCIs, which primarily focus on motor imagery (MI) or cognitive workload, affective BCIs emphasize the detection of emotional and motivational signals derived from neural activity, particularly through non-invasive techniques such as EEG.

EEG measures voltage fluctuations resulting from ionic activity within the neurons of the brain [20]. EEG signals are represented in different frequency bands or ranges [21]: delta (δ , <4 Hz), theta (θ , 4–8 Hz), alpha (α , 8–13 Hz), beta (β , 13–35 Hz), and gamma (γ , >4 Hz); theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (over 30 Hz). Each band corresponds to specific characteristics. The theta band (4–8 Hz) is related to emotional information; the alpha band (8–13 Hz) is related to cognitive processing; the beta band (13–30 Hz) is associated with logical thinking and stimulation effects; while the gamma band (over 30 Hz) is related to memory, linguistic processing, cognition, and attention.

Figure 1 shows that the standard defines 75 electrode positions on the scalp, distributed according to the proportional distance between anatomical landmarks. Electrodes are labeled by both letters – indicating the brain region (F = frontal, C = central, P = parietal, O = occipital, T = temporal) – and numbers or suffixes that differentiate left, right, and midline sites (odd numbers = left hemisphere, even numbers = right hemisphere, “z” = midline).

On the other hand, **Figure 2** shows that the process of integrating BCI technology in STEM education follows a structured pipeline. Whether the goal is to monitor students' attention during problem-solving or provide feedback, the workflow remains consistent: signal acquisition, preprocessing, feature extraction, pattern recognition, decision-making, and feedback. By adapting this structured approach, educators and researchers can systematically integrate BCIs into STEM activities, reinforcing not only technical skills in engineering and computing but also cognitive skills such as attention, memory, and motivation, which are essential for effective learning [22].

Finally, non-invasive BCIs are typically based on three fundamental paradigms that translate brain activity into control signals: P300, MI, and steady-state visually evoked potentials (SSVEPs). Each paradigm exploits distinct neurophysiological mechanisms and has different implications for education and STEM learning.

To better understand the role of EEG in affective BCIs, it is important to highlight how the different frequency bands relate to cognitive and emotional processes. Each band carries distinctive information that can be leveraged in educational contexts, particularly in STEM learning, where attention, memory, and motivation are keys. **Table 1** summarizes the main EEG frequency bands, their functional associations, and their relevance to affective BCIs in education.

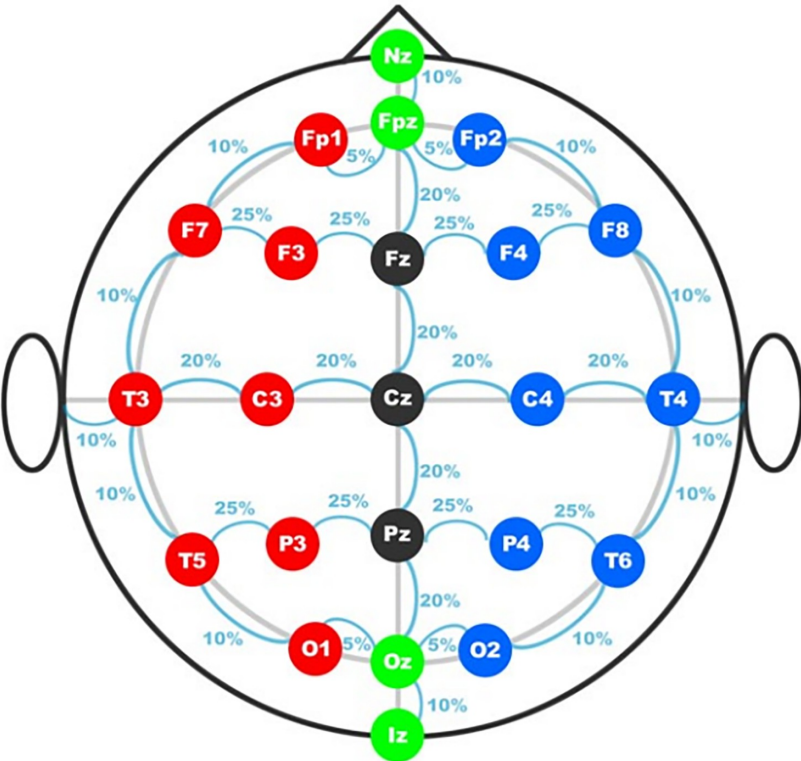


Figure 1.
The standard 75 electrode positions on the scalp, as defined by the international 10–20 system.

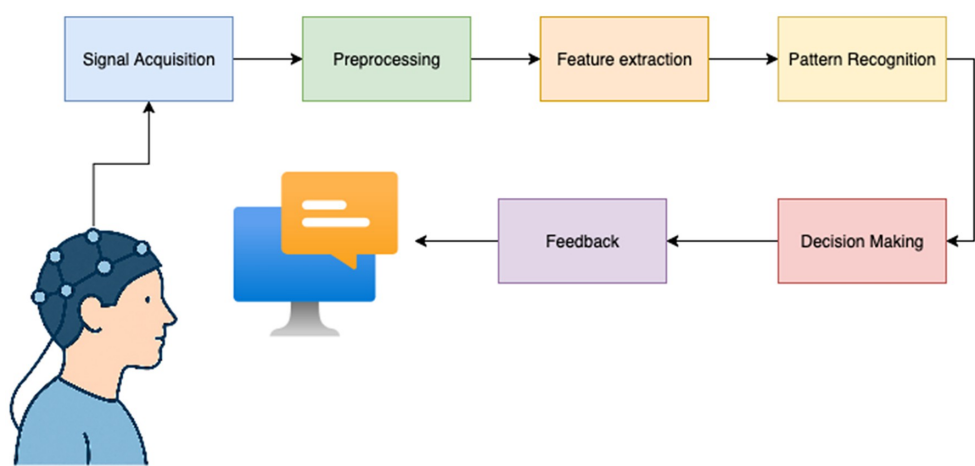


Figure 2.
Summary of the stages of a typical BCI system pipeline.

Band	Frequency range	Associated functions	Lobe	Relevance for education/affective BCIs	
Delta (δ)	< 4 Hz	Deep sleep, unconscious processes, restorative functions.	Frontal (adults), posterior (children) wave of high amplitude.	Less relevant in active learning; useful as a baseline or for detecting fatigue.	[23–25]
Theta (θ)	4–8 Hz	Emotional processing, memory encoding and retrieval, drowsiness.	F _z to C _z	Linked to motivation and emotional information; it is important in monitoring engagement and stress.	[24–26]
Alpha (α)	8–13 Hz	Relaxation, inhibition of irrelevant stimuli, attentional control.	Both hemispheres: P, O, C at rest.	Related to cognitive processing and attention regulation; a marker of relaxed but alert states.	[24, 25, 27]
Beta (β)	13–30 Hz	Logical thinking, active concentration, problem-solving.	F, P, O	Key for STEM learning tasks that require focus and reasoning; it is used in neurofeedback for attention.	[24, 25, 28]
Gamma (γ)	> 30 Hz	High-level cognition, memory binding, linguistic processing, attention.	Somatosensory cortex region.	Associated with working memory, complex cognition, and creativity; highly relevant to STEM problem-solving.	[24, 25, 29]

Table 1.
EEG frequency bands and their educational relevance.

2.2 BCI technologies

BCI technologies are devices that enable direct communication between the brain and external systems by recording, processing, and interpreting neural activity. Non-invasive BCIs rely on sensors placed on the scalp or skin surface, making them safe and widely applicable in educational and STEM environments [30].

BCI technologies have become increasingly popular due to the availability of commercial non-invasive EEG headsets. These devices vary in terms of electrode configuration, sampling rate, portability, and cost, making them suitable for different educational and STEM applications. For example, lightweight single-channel devices are often used in introductory neuroscience or attention-monitoring tasks, while multi-channel research-grade systems enable more complex projects, such as robotics control or adaptive learning platforms. **Table 2** provides a comparison of widely used EEG-based BCI devices – Emotiv, NeuroSky, Muse, and OpenBCI – highlighting their specifications, advantages, limitations, and relevance for educational use.

2.3 BCI and STEM learning

Learning is a cognitive process of acquiring knowledge. A study conducted by Jamil et al. [14] analyzed key factors for enhanced learning in education using BCI

Device	Channels/ electrodes	Sampling rate	Electrode type	Advantages	Limitations	Typical applications
Emotiv (Epoc X, Insight, Flex)	5–32 channels (model dependent)	128–256 Hz	Saline or semi-dry	Research- grade quality; flexible mod- els; strong software ecosystem.	Higher cost: setup can be complex in multi- channel systems.	Attention and workload monitoring; robotics control; classroom demonstrations.
NeuroSky (MindWave)	One channel	~512 Hz	Dry electrode	Very affordable; simple setup; portable.	Very limited spatial reso- lution; high susceptibility to noise.	Introductory experiments; basic attention/ relaxation monitoring.
Muse (Muse 2, Muse S)	Four channels (AF7, AF8, TP9, TP10)	~256 Hz	Dry electrode headband	Comfortable and light- weight; includes motion sen- sors; accessi- ble price.	Limited channels; less precise for advanced signal analysis.	Meditation and attention tracking; classroom focus studies.
OpenBCI (Cytton, Ganglion)	4–16 channels (expandable)	125–250 Hz	Dry or gel-based (customiz- able)	Open source, flexible hard- ware, large community support.	Requires technical expertise; less “plug-and- play” than others.	Robotics projects; advanced STEM labs; experimental prototypes.

Table 2.
EEG frequency bands and their educational relevance.

technology. Through BCIs, it is possible to measure cognitive processes such as memory [31], workload [32], attention, and language [33], as well as affective processes including emotion and motivation. These capabilities highlight the dual potential of BCIs: not only to capture mental states associated with information processing but also to assess the emotional and motivational dimensions that strongly influence learning outcomes. A study conducted by Verkijika and De Wet [34] employed BCI devices to record brain activity in real time and provide students with visual feedback as their anxiety levels increased. In STEM education, this process emphasizes critical thinking, problem-solving, and the integration of interdisciplinary concepts. As educational paradigms increasingly adopt technology-enhanced approaches, BCIs emerge as a promising tool to support and enrich STEM learning.

BCIs provide unique opportunities to connect with education by enabling direct access to cognitive and affective states during the learning process. For example, EEG-based BCIs can detect levels of attention, mental workload, or emotional engagement in real time, offering objective measures that complement traditional assessments. This capability is particularly valuable in STEM disciplines, where students often face cognitively demanding tasks such as programming, mathematical modeling, or engineering design. By monitoring neural activity, BCIs can inform adaptive learning systems that adjust task difficulty or feedback according to the learner’s state, fostering a more personalized and effective learning environment.

Moreover, BCIs can serve as hands-on tools for experiential learning. Students can visualize their brainwaves, use neural signals to control robots, or interact with virtual laboratories, thereby bridging abstract concepts in neuroscience, computing, and engineering with tangible experiences. Such activities not only promote deeper conceptual understanding but also enhance motivation and curiosity, which are key drivers of STEM learning. Robotics, in particular, provides a fertile ground for BCI applications, as learners can observe in real time how their mental states influence the behavior of a physical system, reinforcing both technical and cognitive skills.

2.4 State-of-the-art

EEG provides millisecond-level temporal resolution; it is particularly suitable for capturing rapid changes in cognitive states such as attention training [35], workload [36], and engagement, which are highly relevant in learning environments. BCIs can be relevant to understanding how students learn most effectively [6].

Jiang et al. [22] note that recent advances in wearable and portable BCIs provide opportunities for practical implementation in educational scenarios. Their work highlights how researchers have explored BCI applications not only with students who have mild disabilities but also with healthy learners, focusing on four key areas: memory and attention, spatial and visuospatial skills, collaboration and communication, and creativity and emotional regulation [22]. Similarly, another study reports that BCIs can serve as a potential tool beyond the treatment of physical disabilities by enhancing learning, supporting cognitive functions, and assisting students in their educational activities [37]. A study explores the impact of augmented reality (AR) in educational settings by integrating BCI to evaluate student's attention in real time. In this experiment, participants used AR systems while wearing an EEG headset; the NeuroSky BCI component tracked attentional fluctuation, allowing the results to suggest that AR combined with BCI can provide immediate feedback on attentional states, potentially enabling educators to adapt content or interaction dynamically when attention drops [38]. Ghergulescu and Muntean [39] present a novel EEG sensor-based methodology that supports real-time, non-disturbing automatic measurement and analysis of learner motivation in a game-based learning environment. Their approach uses sensors to capture EEG signals while learners engage with educational games and applies algorithms to infer motivational states without interrupting the learning process. This method is particularly relevant for STEM education, where learner motivation can fluctuate rapidly and influence performance in complex problem-solving tasks. By embedding motivational measurement seamlessly within game interactions, this study demonstrates how affective BCIs can be leveraged to provide insights into student engagement, allow adaptive interventions, and ultimately enhance the learning experience without detracting from it.

3. Methodology

This chapter follows a systematic literature review methodology based on PRISMA 2020 guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [40]. The objective was to identify and synthesize research on the

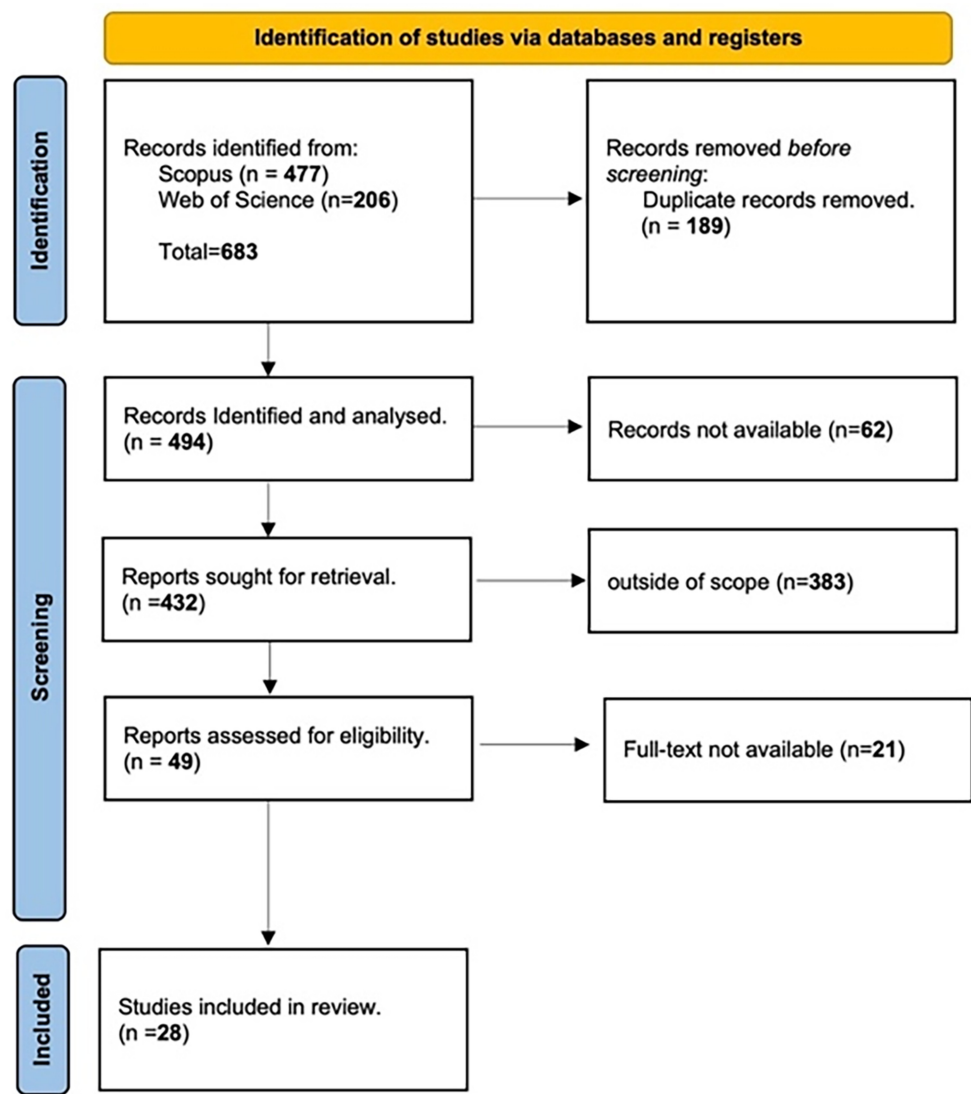


Figure 3.
PRISMA flow diagram.

application of EEG-based BCIs in STEM education, with a particular emphasis on affective and cognitive dimensions. **Figure 3** shows the PRISMA flow diagram applied.

After applying the search strategy, inclusion and exclusion criteria, and conducting full-text screening, a total of 29 articles were selected for the final synthesis. These studies form the evidence base discussed in the following sections.

3.1 Search strategy

Two major academic databases were selected for the search: Scopus and Web of Science, as they provide comprehensive coverage of peer-reviewed journals,

conference proceedings, and multidisciplinary sources relevant to education, neuroscience, and computing. The search string combined keywords related to EEG, BCI, education, affective computing, and STEM. Boolean operators and truncations were adapted to each database's syntax to ensure accuracy.

The search covered publications from January 2020 to September 2025, providing a five-year window that captures the most recent developments in EEG-BCIs applied to learning environments.

Search String = (*"brain computer interfaces"* OR *"bci"*) AND (*"STEM"* OR *"STEAM"* OR *"robotics education"* OR *"STEAM"* OR *"education"* or *"teaching"*, or *"learning"*).

This formulation ensured that the search included studies explicitly referring to BCIs, while also broadening the scope to cover diverse educational contexts such as STEM, STEAM, robotics education, and general educational frameworks. The query was applied to the title, abstract, and keyword fields in each database.

3.2 Inclusion and exclusion criteria

The review included peer-reviewed articles published between January 2020 and September 2023, written in English, that applied EEG-based BCI technology in educational or STEM/STEAM contexts, addressing cognitive or affective processes such as attention, memory, motivation, or engagement.

Exclusion criteria were review papers, gray literature, clinical or non-educational studies, duplicates, and articles without full-text availability.

3.3 Research questions

The review is guided by the following research questions:

- **RQ1:** What applications of EEG-based BCIs have been reported in STEM and educational contexts?
- **RQ2:** Which cognitive and affective processes (e.g., attention, memory, motivation, engagement) are most frequently addressed by EEG-based BCIs in education?
- **RQ3:** What types of technologies, tools, and paradigms are used in EEG-based BCI applications for STEM learning?
- **RQ4:** How can EEG-based BCIs, when combined with affective computing and machine learning methods, contribute to more adaptive and inclusive STEM learning environments?

4. Results

RQ1. What applications of EEG-based BCIs have been reported in STEM and educational contexts?

EEG-based BCIs are being applied in education mainly in four domains: first, attention and engagement monitoring, where consumer-grade EEG headsets (e.g., Muse, Emotiv) are employed in classrooms, online learning, and AR inquiry tools to

provide real-time neurofeedback on students' attention levels. Studies have demonstrated that integrating attention feedback into learning activities can improve science performance, flow, and self-efficacy in primary education [38, 41]. The second domain is neurofeedback for inclusion, where mobile EEG-based games and training tools are used to support children with autism spectrum disorder (ASD), enhancing social attention, motivation, and interaction through playful, multisensory environments [39]. The third domain involves robotics and engineering practice, in which EEG signals, often combined with electromyography (EMG) or machine learning classifiers, enable students to control robots or external devices. Projects such as PlatypOUs exemplify this application by engaging learners in hands-on experiences with robotics and neurotechnology [42], while high-school workshops using blocks or flow-based programming with EEG headsets have increased student's self-efficacy and interest in STEM through practical exposure to human-machine interfaces. The fourth domain includes emotion recognition and educational neuroscience, where EEG signals are analyzed through computational models to classify affective states. Such studies explore how the brain learns, processes emotion, and adapts to instruction, providing insight into the integration of educational neuroscience within BCI systems [42, 43].

Additionally, affective computing integrations combine EEG with other physiological or behavioral modalities, such as facial expression or voice data, to classify emotions relevant to adaptive learning. Beyond the technological domain, emerging ecosystem studies highlight the need to prepare pre-service teachers for this paradigm shift by fostering positive attitudes, self-efficacy, and technological competence to enable inclusive and data-informed classrooms.

RQ2: Which cognitive and affective processes (e.g., attention, memory, motivation, engagement) are most frequently addressed by EEG-based BCIs in education?

Across the reviewed studies, the most frequently explored cognitive process is attention, followed by engagement, memory, and motivation. EEG-based BCIs are primarily employed to measure, monitor, and enhance learners' cognitive states in real time, allowing researchers and educators to better understand how mental focus, emotional regulation, and motivation shape learning outcomes. Attention is the most commonly targeted construct, appearing in nearly all empirical applications. Consumer-grade EEG devices such as Emotiv [44] and Muse [38, 43, 45] have been used to classify attentive versus inattentive states in both online and classroom settings. For instance, Al-Nafjan and Aldayel [46] achieved 96% classification accuracy when distinguishing attention levels during e-learning using spectral EEG features and Random Forest (RF) algorithms. Similarly, Cai et al. [38] demonstrated that incorporating real-time EEG-based attention feedback into AR science inquiry activities significantly improved students' science performance, self-efficacy, and flow, without increasing cognitive load [38].

Engagement and motivation are also key affective processes explored through EEG-based BCIs. In [41], it was found that the use of AR books increased interest and engagement in higher education students, with interest rising in 66% of participants and excitement in 50% [43]. Yan et al. [47], focusing on children with ASD, showed that EEG-based neurofeedback games enhanced social motivation and play engagement, highlighting the inclusive potential of neuroadaptive systems (NASs).

In terms of memory and cognitive workload, EEG spectral analysis has been used to investigate brain activity during mathematical problem-solving and working memory tasks. Trigka et al. [48] identified clear differences in beta activity between

field-dependent and field-independent learners, suggesting EEG as a viable tool for personalized learning and cognitive style modeling. Likewise, Kodai et al. [49] found that learners with higher mathematical performance exhibited greater theta-band activity, correlating with stronger memory retrieval and metacognitive awareness.

Lastly, studies examining emotional states and self-efficacy indicate that EEG can detect affective fluctuations during learning. For example, in [43], valence-arousal mapping was applied to assess emotional responses across manual, CAD-based, and 3D design activities, revealing distinct neural patterns linked to cognitive workload and enjoyment. Together, these studies confirm that EEG-based BCIs offer a multifaceted approach to investigating and enhancing learners' cognitive and affective processes, supporting more adaptive and personalized learning environments.

RQ3: What types of technologies, tools, and paradigms are used in EEG-based BCI applications for STEM learning?

The reviewed studies reveal a diverse ecosystem of technologies, tools, and experimental paradigms underpinning EEG-based BCIs in education. Most applications rely on non-invasive EEG headsets, with consumer-grade devices such as Muse, Emotiv, NeuroSky, MindRove, and OpenBCI predominating due to their portability, affordability, and accessibility for classroom and laboratory use. These devices have enabled studies to be conducted in authentic educational environments, including primary and secondary schools, universities, and special education centers. Common machine learning models include support vector machines (SVMs), k-nearest neighbors, RF, and convolutional neural networks (CNNs). For example, Al-Nafjan and Aldayel [46] achieved 96% accuracy in classifying attentive versus inattentive states in e-learning using EEG spectral features and RF classifiers. Similarly, Echtioui et al. [50] used ensemble learning (SVM + Decision Tree + ANN) for MI EEG classification. These computational approaches enable real-time monitoring and adaptive feedback in educational settings. Regarding paradigms, most educational EEG-based BCI studies are passive BCIs, which capture and interpret learners' spontaneous brain activity without requiring intentional control. They are used for attention tracking, emotion recognition, and cognitive load measurement in learning environments. Fewer studies apply active paradigms, such as MI and SSVEPs, which allow users to control external devices (e.g., robots or cursors) through deliberate thought.

RQ4: How can EEG-based BCIs, when combined with affective computing and machine learning methods, contribute to more adaptive and inclusive STEM learning environments?

Combining EEG-based BCIs with affective computing and machine learning provides a powerful framework for adaptive and inclusive STEM education. This integration enables systems to detect learners' emotional and cognitive states, such as attention, engagement, motivation, and anxiety, and dynamically adjust content, pacing, or feedback.

Several studies demonstrate this potential, such as [16, 19, 51]. In [51], a multimodal affective computing framework was applied that fused EEG, facial expressions, and audio data using a dual-channel long short-term memory (LSTM) model, achieving 75.8% accuracy in emotion recognition and providing a foundation for adaptive e-learning. Similarly, Şekerci et al. [43] utilized Muse2 EEG to measure learners' valence and arousal during design education tasks, showing that emotional feedback can guide personalized teaching strategies. These works illustrate how multimodal affective systems can transform EEG signals into actionable feedback to optimize learning experiences.

In inclusive education, the combination of EEG-based BCIs and ML has been particularly valuable for supporting neurodiverse learners. In [47], mobile EEG neurofeedback games were developed for children with ASD, which significantly improved social attention, motivation, and engagement through adaptive game mechanics. Such systems demonstrate how BCI-enhanced learning can move beyond observation to intervention, providing personalized feedback loops that reinforce positive cognitive and emotional states. Adelana et al. [52] explored teacher readiness for adopting BCI technologies through ML-based predictive models. Their study identified attitude, self-efficacy, and social norms as the strongest predictors of pre-service teachers' readiness to use BCIs in inclusive classrooms. This highlights the need for professional development that prepares educators to integrate affective and neuroadaptive technologies responsibly and effectively.

Machine learning techniques play a central role in this convergence. Algorithms such as SVMs, CNNs, and ensemble models are used to classify EEG and multimodal data into cognitive and affective categories, enabling closed-loop adaptive systems that respond instantly to changes in learner states. These data-driven insights allow educators to visualize engagement trends or cognitive fatigue, while students benefit from personalized scaffolding and feedback. Overall, combining EEG-based BCIs with affective computing and ML contributes to the development of neuroadaptive educational ecosystems that are: (1) adaptive – dynamically adjusting content and feedback to learners' real-time cognitive and affective states; (2) inclusive – supporting diverse learners, including those with ASD or attention difficulties, through individualized neurofeedback; and (3) empowering – equipping teachers with data-driven insights to foster emotional awareness and differentiated instruction (**Table 3**).

	Educational context	EEG device/ technology	Cognitive/ affective process	Methodology paradigm	Key findings
[53] 2020	Online learning and virtual experiment systems	Proposed framework integrating BCI, AI, Big Data, VR, 6 G.	Emotion recognition, attention, and motivation.	Conceptual framework and review of computing applications.	Affective computing combined with online education.
[50] 2021	BCI competition dataset	EEG (118 channels).	MI (hand movement imagination).	Feature extraction + ensemble learning.	Only tested the algorithm.
[51] 2023	Distance education, MOOCs, HCI/ BCI contexts	Multimodal (audio + facial expressions + LSTM-based framework).	Emotion recognition (music-induced emotions, arousal-valence space).	Dual-channel LSTM with analytic hierarchy process fusion.	Only tested the algorithm: integrated into the affective computing framework.
[44] 2024	Mainstream education (K-12, higher)	Multiple BCI devices (Emotiv, NeuroSky, Muse).	Attention, memory, motivation, engagement, stress, anxiety.	Empirical studies.	Prototype BCI regulation system for learning.

	Educational context	EEG device/ technology	Cognitive/ affective process	Methodology paradigm	Key findings
[54] 2025	Educational applications of BCI and ethics.	-	Ethics, privacy, fairness, attention, learning enhancement.	Conceptual analysis.	Discussion of ethical challenges of BCIs in education.
[45] 2020	High school STEM education (10th–11th grade, USA)	Muse EEG (four channels) integrated with neuroflow (block-flow visual programming).	Attention, engagement, BCI self-efficacy.	Hybrid block-flow programming environment; one-day camp study with 14 students.	Demonstrated feasibility of using EEG to teach BCI concepts in STEM contexts.
[47] 2021	Preschool children with ASD.	Mobile EEG headband.	Attention, social engagement, and mirror neuron activation.	Industry–academia collaboration, iterative design of neurofeedback training games.	Neurofeedback for ASD.
[55] 2025	Conceptual reform in AI and education.	BCIs + AI (Neuralink, NASS, VR labs).	Autonomous learning, cognition, equity, computing power.	Literature review, case study, technology trend analysis.	Explores AI + BCI integration in education: BCIs may enable instant knowledge input, reshape cognition, and shift power.
[38] 2022	Primary science education	Muse2 EEG + AR environment.	Attention, flow, self-efficacy, cognitive load.	Quasi-experimental field study.	Student using BCI-based AR tool with real-time attention feedback.
[52] 2024	Inclusive classrooms, pre-service teacher training (Nigeria).	Conceptual BCI readiness.	Attitude, self-efficacy, subjective norm, assistive technology knowledge.	Survey of 320 pre-service teachers + Decision Tree ML analysis.	Only tested algorithm model: Attitude was the strongest predictor of readiness.
[41] 2016	Higher education, engineering students	Emotiv insight.	Emotional states: engagement, stress, interest, relaxation, excitement, concentration.	Comparative experiment: traditional text vs. AR book working with pre-service teacher.	BCI captured differences in emotional variables.
[56] 2022	Basic science education (biomedical training)	NeuroSky MindWave + HoloLens (ARNIE platform).	Attention, engagement in AR tasks.	Proof-of-concept integration of AR and BCI.	Developed ARNIE (AR and neurosensing interaction environment).

	Educational context	EEG device/ technology	Cognitive/ affective process	Methodology paradigm	Key findings
[57] 2024	Educational games/serious games (STEM and HCI research)	EEG-based BCI (consumer-grade and research-grade).	Attention, meditation, cognitive workload, game experience.	Theoretical framework for representing and developing studies based on BCI games.	Conceptual contribution highlights design and research challenges in BCI educational games.
[58] 2020	Primary School education (Children's cognitive processes)	EEG, fMRI, portable EEG.	Memory, attention, writing, and mathematics skills.	Literature review of ~ 30 + studies on brain activity in learning (5–6 years).	Studies focused on short-term EEG testing (attention, memory, math, reading).
[59] 2022	Machine learning education	EEG MI dataset	Engagement self-efficacy, ML concept understanding.	Gamified web-based system with three levels: data collection, model training, and model evaluation.	Developed MTeacher, a gamified system that uses physiological EEG data to teach machine learning (ML).
[43] 2024	Interior architecture education	Muse 2EEG (four channels: TP9, AF7, AF8, TP10).	Emotional states: valence, arousal.	Experimental design using the circumplex model to analyze emotions (arousal-valence).	Emotional profiles associated with positive high-arousal emotions.
[60] 2024	Neuroeducation	EEG, fMRI, MEG, NIRS (review of multiple neuroimaging tools for BCI).	Attention, memory, motivation, emotion, neuroplasticity.	Theoretical synthesis (neuroplasticity, action-control theory).	How neural dynamics, synaptic plasticity, and neurotransmitter activity underpin learning?
[48] 2024	E-learning personalization, university students	Biosemi EEG (32 channels, 2048 Hz, down-sampled to 512 Hz).	Cognitive style, attention, problem-solving.	EEG preprocessing and features extraction.	Preliminary findings with the BCI system to analyze cognitive style.
[1] 2024	NeuroEducation (primary and secondary school students)	LiveAmp EEG (64 channels, brain products).	Executive functions, attention, working memory, cognitive flexibility, fatigue.	EEG-based open-loop NAS integrating behavioral and neurophysiological data.	Open-loop NAS to assess and enhance cognitive abilities through personalized recommendations.
[42] 2022	Robotics and STEM education	MindRove BCI headset (EEG/ EMG, 6 channels).	Attention, engagement, and control learning.	Experimental development: EMG/ EEG signal acquisition, SVM classification, and mobile robot control.	PlatypOUs, an open-source mobile robot platform controlled by EEG/ EMG signals via an SVM classifier.

	Educational context	EEG device/ technology	Cognitive/ affective process	Methodology paradigm	Key findings
[61] 2024	Game-based learning /engineering education	OpenBCI Cyton (eight channels, 250 Hz).	Engagement index (EI), attention, eye blink (control).	Rapid prototyping approach using Timeflux for EEG processing and Unity for feedback.	BCI game controlled by blink detection and engagement index (EI).
[46] 2022	Online learning (higher education, e-learning)	Emotiv EPOC EEG dataset (12 channels: alpha, beta, theta, gamma bands).	Attention monitoring.	EEG signal preprocessing (band-pass 2–40 Hz, ICA artifact removal); PSD feature extraction; ML classification.	EEG-based attention detection system for e-learning. Beta activity is most correlated with attention.
[49] 2020	High school mathematics	EEG system (128 channels, 250 Hz).	Mathematical performance, theta activity, problem-solving, confidence.	Experimental study with 14 high school students performing estimation and solving phases for math problems.	Participants with higher mathematical performance showed greater theta-band activity during problem estimation.
[62] 2020	Educational technology (HCI and immersive learning)	Kinect + VR/AR integration.	Engagement, motivation, cognitive load.	Kinect and VR use in education.	No EEG was used; the study contextualizes BCI's role in multimodal learning.
[63] 2021	Preschool and primary education (mathematical ability development)	EEG, fMRI (review of non-invasive methods).	Mathematical ability, number processing, working memory, and attention.	Neurocognitive mechanism of mathematical development.	BCI-based neurofeedback for math training and the importance of early skill development.
[64] 2023	Higher education	NeuroSky MindWave II (one channel, Bluetooth wireless EEG).	Attention (cognitive focus), gender differences.	Attention data analyzed during two activities – mathematical problem-solving and gaming – using descriptive statistics (mean, max, min).	Girls were more attentive to math tasks, while boys were more attentive during gaming.
[65] 2020	Higher education (educational reading and cognitive monitoring)	Neuron-spectrum EEG system.	Cognitive processes: attention, interest, theta rhythm dynamics.	Experimental study: EEG coherence analysis on FP1–FP2 leads; theta rhythm dominant frequency analysis.	Found that the dominant theta rhythm frequency increased when students read uninteresting or unfamiliar texts and decreased with more engaging content.

Table 3.
Summary of selected studies on EEG-BCIs in STEM education.

5. Conclusions and limitations

Several studies highlight persistent limitations in the current use of EEG-based BCIs, particularly concerning the optimal number and placement of electrodes, the need for reliable calibration and mutual adaptation between user and system, as well as challenges related to signal noise, data quality, and response latency. Additionally, issues of cost, accessibility, and ethical data management remain barriers to large-scale adoption in educational environments.

Despite these challenges, the integration of BCIs in education – especially within STEM disciplines – is showing promising progress. Although still in its early stages of implementation, the evidence gathered across studies suggests that BCIs hold significant potential to transform learning experiences. Their capacity to capture real-time neural and emotional indicators of students' engagement, attention, and motivation opens new opportunities for adaptive feedback, personalized learning, and inclusive educational practices.

Moreover, BCIs have been successfully integrated into interactive applications such as robotics control, neurofeedback-based games, affective computing systems, and immersive AR/VR learning simulations, all of which foster active engagement, creativity, and interdisciplinary problem-solving skills. As research in this field advances, BCIs are expected to evolve from experimental prototypes to scalable educational technologies, enabling the development of neuroadaptive learning environments where instruction dynamically adjusts to learners' cognitive and affective states. In this trajectory, future work should focus on improving hardware ergonomics, algorithmic precision, and teacher training, while addressing the ethical, privacy, and inclusivity dimensions of neurotechnology in education.

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Brain–Computer Interface: Toward an Emancipatory Neurotechnology from the Global South

Clara Elisa Tapia Nin and José Wilson Gómez Cumpa

Abstract

This article explores brain–computer interfaces (BCIs) from the perspective of the Global South, proposing their transformation into emancipatory tools for inclusion, care, and autonomy. It argues that the social value of BCIs depends on anchoring innovation in three key vectors: cognitive sovereignty, which extends data rights to the neural realm with principles of reciprocity and traceability; epistemic justice, which corrects biases in datasets from the Global North to improve generalization in diverse contexts; and situated design, adapting technologies to local realities. On the technical front, it highlights advances such as robust and explainable decoders, online adaptation to reduce calibration, diffusion-based noise removal, and comfortable electrodes for pediatric inclusion, with emphasis on noninvasive electroencephalogram (EEG) in Latin America. It addresses risks like geotechnological asymmetries, data privatization, and neuro-privacy violations, proposing a five-pillar strategy: research with reciprocal licenses, local open-source design, ethical training, regulation via sandboxes, and pilot projects with social impact. Finally, it presents a 2025–2030 roadmap to transition from lab prototypes to sustainable systems, prioritizing metrics of efficacy, safety, and equity under democratic governance, positioning the Global South as a leader in neuro-rights and cognitive dignity.

Keywords: cognitive sovereignty, brain–computer interfaces, epistemic justice, situated neurotechnology, cognitive extractivism, global south

1. Introduction

Brain–computer interfaces (BCIs) have consolidated as a convergence field in neuroscience, engineering, and machine learning (a process by which machines learn data patterns), translating brain activity into commands for devices or communication signals [1, 2]. This technological field has the potential to transform rehabilitation, assisted communication, and learning by enabling direct interaction between the brain and the digital world. Technical progress in recent decades has reduced classic barriers of control, robustness, and latency (response delay), opening the door to applications outside the laboratory environment [3].

However, this dynamism coexists with a landscape of profound inequality, which the authors call the “technological abyss” in neurotechnology (technologies that interact with the nervous system) [4]. Research, development, patents, and advanced hardware and software infrastructure are overwhelmingly concentrated in a handful of power centers in the Global North (developed countries such as the United States, Europe, and China) [5]. This imbalance is evident when examining quantitative data: a bibliometric analysis (quantitative study of scientific publications) from 2010 to 2021 revealed that only 2.7% of scientific publications in neurotechnology journals come from Latin America [6]. Similarly, private investment in artificial intelligence (AI, systems that simulate human intelligence) across the Latin American region does not exceed 1.8% of US investment or 21% of China’s in 2024 [7]. This pattern extends to the development of software tools, such as CiteSpace II (citation analysis tool) and Statistical Parametric Mapping (SPM, software for statistical parametric mapping), as well as pioneering hardware companies like g.tec medical engineering (Austria) and OpenBCI (USA), which are headquartered in developed countries [8].

This concentration of resources and knowledge creates a landscape of inequality that limits independent validation and replication of studies in low- and middle-income settings [9]. The Global South, therefore, faces a dual challenge: leveraging the opportunity offered by new platforms and models while reconfiguring the rules governing the production, circulation, and use of knowledge. Failure to do so could deepen patterns of dependency or cognitive extractivism (exploitation of mental data without local benefits), where neural data from Global South populations are used to train models that provide no direct or proportional benefit to those communities [10]. This article advances a conceptual, technical, and governance architecture that seeks to make neurotechnology a socially anchored and culturally relevant tool, subject to evaluation under public criteria of efficacy, safety, equity, and sustainability [11].

2. Conceptual framework

To guide the analysis and proposed agenda, a conceptual framework of three axes is used, which transcends the technicist view of BCIs, anchoring them in their socio-political context.

First, cognitive sovereignty is defined as an extension of data sovereignty to the neural realm [12]. This principle establishes that individuals and communities retain rights over the capture, processing, inferences, and subsequent uses of their brain activity [13]. Cognitive sovereignty goes beyond a minimalist understanding of consent, often reduced to a simple checkbox on a form. Instead, it incorporates principles of reciprocity, traceability, and benefit-sharing, fundamental elements when research or service provision is based on public institutions or vulnerable user cohorts [14].

Second, epistemic justice addresses the centrality of datasets and standards built from Global North populations and laboratories [15]. Evidence shows that decoders trained in homogeneous contexts tend to generalize poorly in culturally and physiologically diverse environments, with accuracy losses that entail direct clinical and educational consequences [16]. The response to this problem is not merely technical; it requires a fundamental change in research and innovation

design, co-designing protocols and tools with local users, therapists, and educators. In this way, external validity ceases to be an occasional byproduct and becomes an intrinsic design criterion from the start of the process [17].

Finally, the concept of neurodigital complexity underscores that BCIs are not simple artifacts but sociotechnical systems whose real impact depends on “ecologies of use” [18]. This includes a complex network of factors, such as the availability of trained professionals, data infrastructure, institutional organizational culture, and regulatory frameworks, among others [19]. Understanding this complexity is crucial for moving from laboratory demonstrations to sustained technology adoption in the real world. These three concepts (sovereignty, justice, and complexity) act as the analytical keys guiding the critical diagnosis and programmatic agenda developed in this article.

The deep interconnection of these concepts reveals why the technological gap is so harmful. It is not simply a matter of the Global South lacking technology; the existing technology, developed in specific Northern contexts, often functions ineffectively or inequitably for Southern populations [9]. The technical failure of poor decoder generalization thus becomes a matter of social and ethical justice. When the dominant knowledge base (datasets) is not representative, the resulting technology perpetuates existing inequalities. The solution, therefore, does not lie in passive access to technology but in active co-design and localized validation.

3. Methodology

3.1 Design and justification of the research

This chapter is based on a narrative review of the state of the art, a qualitative research method designed to synthesize existing knowledge in a broad and multidisciplinary field of study [20]. This approach was selected for its ability to offer a holistic and integrated reading of a topic as complex and multifaceted as BCIs, encompassing technical advances, ethical frameworks, and geopolitical analyses [21, 22, 23, 24, 25]. Unlike a systematic review, which focuses on a very specific research question and uses strict inclusion and exclusion criteria, the narrative review is ideal for identifying general trends, proposing new conceptual frameworks, and outlining a programmatic agenda [20].

The main objective of this methodology is to make the research process clear and accessible to a broad audience, including beginner researchers in the field. While the final interpretation of the literature may be subjective, transparency in the search and information synthesis process allows other scholars to replicate the process and verify the findings [79]. Additionally, the inherent limitation of subjectivity in narrative reviews is acknowledged but mitigated through the inclusion of quantitative data and cross-references for greater rigor [80].

3.2 Search strategy and data sources

A comprehensive and exhaustive search strategy was implemented. Multiple academic databases and gray literature repositories (unpublished documents such as reports) were consulted to ensure broad coverage of relevant publications. The consulted databases included PubMed (biomedical database), Scopus

(multidisciplinary database), Web of Science (general scientific database), IEEE Xplore (engineering database), and Google Scholar (academic search engine). The search was conducted from January 2018 to September 2025 to capture the most recent advances in the field.

Search queries were formulated using a combination of keywords, including “brain–computer interface,” or “brain–computer interface” combined with focus terms such as “Global South,” or “Global South,” “neurotechnology,” “Latin America,” “neuroethics” (ethics applied to neurosciences), “cognitive sovereignty,” “data governance” (ethical data management), “open hardware” (open-source technology), and “signal processing” (analysis of signal data) [1]. The search was supplemented with a manual review of reference lists from identified seminal articles and a targeted search for policy reports and documents from international organizations such as UNESCO (United Nations Educational, Scientific and Cultural Organization) and OECD (Organization for Economic Co-operation and Development).

The decision to expand the search strategy beyond a single database aligns with the principle of epistemic justice. Limiting the search to a single source can introduce significant bias, excluding relevant literature from other regions, in other languages, or specific domains. By detailing the process and sources, the study enhances its scientific rigor and exemplifies a commitment to a comprehensive and epistemologically fair research approach.

3.3 Selection and synthesis of the literature

Approximately 1,500 initial articles were identified through the consulted databases. After applying inclusion criteria (relevance to the topic, academic quality, recent date, and geographic diversity) and exclusion criteria (duplicates, non-peer-reviewed articles, or irrelevant ones), 75 were selected for the final synthesis, prioritizing those with impact in the Global South.

The collected literature was organized through thematic analysis (classification by themes) to address the multiple dimensions of the central research question. The material was classified into conceptual categories (theoretical framework), technical (state of the art), geopolitical (power asymmetries and governance), and strategic (roadmap and pillars). The document “The Technological Abyss in Neurotechnology: An Analysis of the Gap between the North and the Global South” was used to complement the review with key quantitative data. This material served as a vital source to substantiate macro-level arguments about the technological gap and the emergence of neuro-rights (rights related to the mind and brain) in the Global South. The integration of these quantitative data allowed transitioning from a conceptual diagnosis to an evidence-based critique, connecting abstract problems with concrete numbers of scientific production and investment.

4. Critical diagnosis

The view of technology as inherently neutral has been an obstacle to a justice-oriented perspective in the BCI field. The analysis shows that biases are not limited to the algorithm; they begin in data sampling, continue in signal acquisition, and become rooted in evaluation, especially when laboratory metrics are prioritized over

sustained use indicators in real environments [26]. The technological gap is not an accident but a consequence of inherent biases in the ecosystem, perpetuated by the concentration of patents, infrastructure, and talent [27].

The recent decline in open access to AI data repositories (“data commons,” shared data resources) illustrates how the privatization of these resources reduces transparency and raises verification costs, shifting the burden of proof to actors with fewer resources and limiting independent replication in the Global South [28]. This phenomenon is a direct consequence of investment disparity, where large Global North corporations have the capital to acquire and privatize the most valuable datasets. In this context, the hasty implementation of commercial solutions without domain-specific protections (e.g., in education or welfare) creates risks of neuro-privacy and “brainhacking” (brain hacking, unauthorized manipulation of neural data), ranging from sensitive data leaks to attention profile manipulation [29]. Therefore, the field not only needs engineering standards but also clear rules for responsible experimentation and effective redress mechanisms, aligned with best practices in cybersecurity and research ethics [11].

5. Technical state of the art (emphasis: 2023–2025)

The field of noninvasive BCIs has experienced significant advances in recent years, focusing on improving performance, usability, and accessibility. In signal processing, transformer-type models pre-trained for EEG (electroencephalogram: recording of brain electrical activity) have produced brain activity representations that are more invariant to device differences, sampling rates, and noise levels [30]. This improvement facilitates knowledge transfer between subjects and tasks, reducing dependence on extensive and prolonged calibration [16]. In parallel, online adaptation has shown that decoders can be adjusted during use without interrupting user interaction [31]. The effectiveness of machine learning models used in brain–computer interfaces (BCIs) is often limited by the availability of training data [32]. This capability is crucial for scenarios like rehabilitation and classroom learning, where operation time is limited, and continuity is essential for progress [33]. Diffusion-based noise removal (a probabilistic filtering technique) has improved signal-to-noise ratios without erasing relevant neurophysiological components, translating into performance gains for motor, attentional, and affective tasks [34].

Combined with techniques such as neural symbolic regression (a method combining neural networks with symbolic expressions for interpretability) and recurrent networks (models that process temporal sequences), these advances have unified interpretability and dynamic modeling [35]. This is of great value when the goal is not only to classify a mental state but also to sustain continuous control or synthesize speech with clinically significant latencies [36].

Regarding sensors and materials, the development of electrodes designed for prolonged use has stabilized impedance (electrical resistance) and increased comfort – necessary conditions for studies outside the laboratory and everyday applications [37]. Injectable hydrogels (biocompatible gels) and smart gels have expanded inclusion for pediatric populations and users with skin hypersensitivity, while high-density surface EEG has narrowed the gap with invasive recordings for specific use cases [38]. In Latin America, research has predominantly focused on noninvasive and low-cost technologies, such as EEG, which represented 85% to 94.68% of studies in a recent analysis [5]. This focus is due to advantages like low

cost, ease of use, and no need for special facilities, unlike more expensive and complex modalities such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET), or magnetoencephalography (MEG: recording of brain magnetic fields), which are less common in the region [39].

This focus on EEG is not a sign of technical inferiority but a pragmatic and situated response to infrastructure and resource limitations. The region is innovating within its possibilities, developing inherently more accessible and scalable solutions. This situated design process fosters an open-source hardware and software ecosystem that reduces operation and maintenance costs, making local manufacturing viable [40].

Current BCI applications show differential maturity. Assisted communication is in the validation phase, with speech neuroprostheses (devices that convert thoughts into voice) beginning to meet clinical utility criteria, both with implants and surface recordings [41]. Rehabilitation programs based on motor imagery (mental visualization of movements) continue to report functional gains and measurable changes in cortical activation [33]. In education, EEG integration with cultural practices like music and rhythm has shown positive effects on attention and fatigue, with implications for curriculum design and formative assessment strategies [42]. Recent advances include Neuralink's N1 implant, which enables cursor control for games and digital tasks in volunteer trials, and new noninvasive approaches like micro-sensors between hair for continuous monitoring [10, 43].

6. Geopolitics, political economy, and data governance

BCIs have become a terrain of strategic competition [44]. Whoever controls technical standards, data flows, and talent training will establish reference frameworks and capture the surplus. The concentration of patents and capital, dependence on chip and sensor supply chains, and the growing value of neural repositories draw a map of power with persistent asymmetries [4]. Quantitative data reaffirm this reality: joint private investment in AI across all Latin American countries does not exceed 1.8% of US investment or 21% of China's in 2024, severely limiting the Global South's capacity to compete in the technological race [7].

In this context, the South's response cannot be limited to demanding access; it must build institutional alternatives [10]. A layered governance architecture (data, infrastructure, algorithms, and talent) helps delineate responsibilities and control mechanisms [45]. This includes complementing FAIR principles (Findable, Accessible, Interoperable, Reusable) with CARE principles (Collective Benefit, Authority to Control, Responsibility, Ethics) for communities [46]. The agenda is compatible with OECD regulatory regimes and Europe's digital rights trajectory, and can leverage South-South agreements to reduce risks posed by sanctions and export controls on critical inputs [47].

7. Regulatory frameworks and neuro-rights

Regulatory progress has moved from general principles toward more operational instruments [45]. The constitutional protection of brain information

and psychic integrity in Chile has established a regional benchmark, while Colorado's law on consumer brainwaves has opened the debate on non-clinical commercial uses and the need for domain-specific consent and limits [48]. This Chilean initiative, as the first country in the world to legislate and protect the human mind at a constitutional level, seeks to create a "legal wall" to safeguard psychic integrity, mental privacy, and free will [49]. In collaboration with neuroscientists like Rafael Yuste, five fundamental neuro-rights have been proposed for incorporation into the Universal Declaration of Human Rights: the right to personal identity, the right to free will, the right to mental privacy, the right to equitable access, and the right to protection against biases and discrimination [11]. By 2025, states like California and Montana have followed with similar laws requiring express consent for neural data, and UNESCO has advanced toward a global ethical standard for neurotechnology [50].

This contribution demonstrates that leadership in neurotechnology is not defined solely by technical production. The Chilean initiative is a clear example of how the Global South can lead the ethical debate and the construction of a global legal framework, inverting the traditional dynamic where norms are imposed by the North [51]. The absence of commercial pressure existing in the Global North grants the South a unique opportunity for proactive and preventive governance. The Global South can establish the ethical and legal foundations that will guide technology development worldwide, contributing significantly to the dignity and human rights of future generations [18].

8. Education, literacy, and epistemic change

Without critical education, neurotechnology remains a topic for specialists; with literacy, it can become a care policy [52]. The learning pathway begins in school with basic neuroscience, notions of privacy and biases, and responsible practices with portable devices [53]. It continues in technical education with instrumentation, assembly, and data flow management [51]. The path culminates at the university level with subjects on signals and systems, AI applied to EEG, neuroethics, and digital law [12]. Continuing education for clinicians, therapists, and teachers must integrate applied BCI modules and impact assessment, in line with UNESCO guidance and approaches inspired by FATE (Fairness, Accountability, Transparency, and Ethics) [46]. Evaluation must go beyond "does it work?" to include measures of sustained adoption, satisfaction, and comfort, so that technical success aligns with user experience and clinically and educationally relevant outcomes [54].

9. A sovereign cognitive strategy: Five articulated pillars

The strategy seeks to turn criticism into installed capacity. Pillar 1: Research and data foster regional networks; build benchmarks in motor, speech, and affective domains; and develop repositories with dataset cards, reciprocity-based licenses, and traceability. By prioritizing underrepresented populations and pediatric stages, this strategy improves generalization and corrects biases from the source [38].

Pillar 2: Local design and manufacturing promote open-source hardware and software, low-code libraries for clinical and classroom professionals, auditable firmware, and nearby maintenance services that reduce downtime and operating costs [40]. Pillar 3: Neurodigital training and literacy combine MOOCs (Massive Open Online Courses), intensive courses, and technical programs with trainer training pathways and inclusion objectives [52]. Pillar 4: Regulation and cooperation align standardized impact assessments, risk-class certification authorities, South–South data and technology exchanges, and supervised controlled environments with output metrics and regulatory feedback circuits [45]. Pillar 5: Pilot projects with social return focus on rehabilitation, assisted communication, and EEG-assisted learning, with efficacy evaluation and longitudinal follow-up [50]. The decisive step is converting pilot projects into sustainable services within health and education systems, with stable funding and continuous improvement mechanisms [55].

10. 2025–2030 roadmap and risk management

10.1 Elucidation of the probability and impact matrix

The “Probability and Impact Matrix of Strategic Risks in BCI Development for the Global South” (see **Table 1**) is a risk assessment tool (PIM, for Probability Impact Matrix) that allows for visualizing, evaluating, and prioritizing potential threats based on their probability of occurrence and the severity of their impact [81]. This methodology transforms conceptual risks into concrete and quantifiable threats that can be strategically managed.

The matrix construction followed these steps:

- (1) Risk identification: Risks were identified through thematic analysis of the reviewed literature, covering technical, geopolitical, and ethical risks. Threats

Strategic risk	Probability (1–5)	Impact (1–5)	Risk score	Proposed mitigation (Pillar)
Data extractivism	5 (almost certain)	5 (catastrophic)	25 (high)	Reciprocity licenses, sovereign infrastructure (Pillar 1)
Epistemic bias	4 (likely)	4 (critical)	16 (high)	Dataset diversity, regional benchmarks (Pillar 1)
Supplier dependency	4 (likely)	5 (catastrophic)	20 (high)	Open-source hardware and software, portability clauses (Pillar 2)
Talent shortage	4 (likely)	4 (critical)	16 (high)	MOOCs, technical programs, trainer training (Pillar 3)
Fragmented governance	3 (possible)	3 (marginal)	9 (medium)	Controlled environments, impact assessments (Pillar 4)
Lack of adoption	3 (possible)	4 (critical)	12 (medium)	Pilot projects, usability metrics (Pillar 5)

Table 1.
Probability and impact matrix of strategic risks in BCI.

such as data extractivism, epistemic bias, supplier dependency, and talent shortages were included.

- (2) Scale definition: 5-point scales were defined for “Probability” and “Impact,” with qualitative criteria for each level [83].
 - Probability (likelihood): Classified on a scale from 1 to 5, where 1 corresponds to a rare event (less than 10% probability) and 5 corresponds to an almost certain event (more than 90%) [83].
 - Impact (severity): Classified on a scale from 1 to 5, considering consequences in four main dimensions: social impact (e.g., harm to dignity or rights), financial cost (e.g., dependency or blockade), regulatory compliance (e.g., privacy violations), and reputational damage (e.g., loss of public trust) [81].
- (3) Risk calculation: The overall risk score was calculated by multiplying the probability score by the impact score ($\text{Risk Score} = \text{Probability} \times \text{Impact}$) [81].
- (4) Color coding and prioritization: Results were represented in the matrix using a color-coding system (green for low risk, yellow for medium risk, red for high risk), allowing quick identification of the most critical risks requiring immediate attention [82].

This methodology provides a structured view for risk management, ensuring that the strategy proposed in Section 9 is a targeted response to the most significant threats. The “Risk Score” is a quantitative indicator derived from multiplying Probability and Impact, where values greater than 15 indicate high risks requiring immediate mitigation.

The system-level transition requires clear phases. The 2025–2026 stage (Foundations) focuses on forming a regional consortium, opening controlled environments, and validating open-source prototypes in real-use scenarios. The 2027–2028 phase (Scaling) seeks to consolidate risk-class certification, deploy pilot projects in hospitals and schools, and operate a regional sovereign cloud with end-to-end encryption. Finally, the 2029–2030 stage (Consolidation) focuses on incorporating BCI content into curricula and expanding coverage in hospital and school networks.

10.2 Risk management

To prevent data extractivism, the strategy relies on adopting reciprocity licenses, sovereign infrastructures, and independent audits. To mitigate bias, it seeks to strengthen dataset diversity, transfer learning, and regional benchmarks. To reduce vulnerabilities, end-to-end encryption deployment and zero-trust architectures (a “zero-trust” security model without implicit trust) are proposed. To avoid supplier dependency, the use of open standards and portability clauses in public procurement is required. Finally, to maintain social acceptance, investment is made in community participation, transparency, and effective redress mechanisms.

11. Conclusions

The question underlying this work is not merely technical but profoundly political: What kind of neurotechnology do we want, and for whom? If the Global South limits itself to accepting the terms of the race for patents and closed repositories, BCIs will reproduce hierarchies of extraction and dependency [9]. However, if it advances with an agenda of sovereign data, context-sensitive design, and critical education, the conversation will shift from spectacular demonstrations to services that genuinely improve lives without compromising dignity or cognitive freedom [11]. The Global South has the opportunity not to lead in the technological race, but in building governance frameworks that ensure these advances serve the well-being of all humanity [14].

The 2025–2030 window is narrow but sufficient. There is already accumulated knowledge, an emerging ethical framework, and institutional will to build fairer governance [46]. Success will depend on universities, hospitals, schools, regulators, and communities acting as an interconnected system rather than as isolated entities. The bar for success is demanding and clear: measurable efficacy, verifiable safety, demonstrable equity, and sustained public trust.

Nomenclature and abbreviations

BCI	Brain–computer interface
EEG	Electroencephalography
ALS	Amyotrophic lateral sclerosis
FAIR	Findable, Accessible, Interoperable, Reusable
CARE	Collective Benefit, Authority to Control, Responsibility, Ethics
FATE	Fairness, Accountability, Transparency, Ethics
EU	European Union
OECD	Organization for Economic Co-operation and Development
UNESCO	United Nations Educational, Scientific, and Cultural Organization
ReHandBCI	Latin American stroke-rehabilitation BCI trial

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Chapter 3

The Performance Triad: Cognitive Readiness, Situational Awareness, and Willpower in Adaptive Learning Systems – Operationalizing Cognitive Readiness, Situational Awareness and Motivation Through Brain-Computer Interfaces

Curtis Cripe

Abstract

What if a user could steady performance before it slips? This chapter shows how brain-computer interfaces (BCIs) turn that promise into practice by making three essentials – cognitive readiness (planning and flexibility), situational awareness (perceiving what matters), and motivation/willpower (sustained effort) – measurable, coachable, and coordinated in real time. This chapter introduces a vendor-agnostic, closed-loop “anticipate → cue → lockout → learn” policy that forecasts near-term lapse risk (3–10 seconds ahead), delivers a single well-timed micro-intervention, and then audits what it prevented (e.g., prevented-lapse rate, lead-time, intervention yield). Readers get a clean theory-to-operations bridge: classic foundations – Rasmussen’s skills-rules-knowledge (SRK) control framework, spacing and retrieval practice from learning science, and cognitive load theory – are translated into concrete loop actions; network connectivity explains why even high-ability people falter under stress; and a trait-state-motivation profile personalizes training over weeks, not just minutes. SRK clarifies when to automate versus assist; spacing/retrieval shapes micro-interventions that stick; and Cognitive Load sets task and UI constraints so cues help rather than hinder. Applications span classrooms, flight and mission operations, surgical training, rehabilitation, athletics, and high-stakes decision-making – each using the same control logic with domain-specific tuning. The authors close with evaluation designs (AB/ABA, crossover) and clear ethical guardrails (privacy, transparency, equity). The result is a practical playbook for researchers, educators,

clinicians, and operators who need resilient, auditable gains – when performance under pressure really matters.

Keywords: brain–computer interfaces (BCIs), EEG connectivity biomarkers, predictive early warning, adaptive closed-loop training, situational awareness

1. Introduction

For much of modern educational history, learner assessment and intervention have been guided by the premise that performance outcomes and behavioral indicators are sufficient proxies for cognitive function. Teachers, trainers, and psychologists have relied on observable behavior, periodic testing, and learner self-reports to identify skill gaps and intervene [1]. While these approaches have yielded valuable insights, they are inherently reactive; interventions occur only after a lapse, error, or performance decline has already manifested [2].

In parallel, decades of research in cognitive psychology and human factors have produced rich theoretical models of how humans acquire skills, adapt to new environments, and maintain performance under pressure. Theories such as cognitive readiness (CR) [3], situational awareness (SA) [4], the SRK framework [5], and the Ebbinghaus forgetting curve [6] have shaped the authors’ understanding of learning and performance. Yet, until recently, these models have remained largely conceptual in educational contexts, lacking mechanisms for continuous, real-time measurement and adaptive response.

The emergence of advanced brain–computer interfaces (BCIs) has changed this landscape. BCIs allow for the direct measurement of neural activity and connectivity patterns during learning, enabling an unprecedented view into the learner’s cognitive state and capacity at any given moment [7]. The integration of EEG-based systems into training environments operationalizes theoretical constructs into dynamic, measurable, and adaptive protocols [8, 9].

This chapter presents an integrated framework that distinguishes between *cognitive traits* – relatively stable capabilities such as working memory capacity or baseline executive function – and *cognitive states*, which are transient, moment-to-moment variations in attention, arousal, or mental fatigue [8, 10]. This trait–state distinction is critical for designing adaptive learning systems: traits determine the learner’s baseline capacity, while states modulate real-time performance within that capacity.

The author extends this framework by introducing a third and equally essential element: motivation/willpower. Alongside readiness and awareness, motivation forms part of what the author terms the Performance Triad, as shown in **Figure 1**. Each leg of this triad is necessary but not sufficient on its own:

- **Cognitive readiness (CR):** the ability to plan and adapt flexibly.
- **Situational awareness (SA):** the ability to perceive and interpret environmental cues.
- **Motivation/willpower:** the persistence of effort, emerging from the alignment of intent (direction), motivation (energy), and capacity (resources).

The Performance Triad Framework

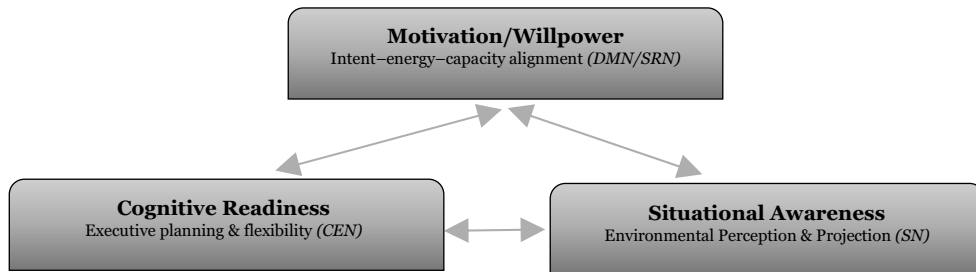


Figure 1.
High performance emerges when readiness, awareness, and motivation networks synchronize dynamically to sustain effort and adaptability.

Neurobiologically, this triad is grounded in large-scale brain networks: the central executive network (CEN) supports readiness, the salience network (SN) supports awareness, and the default mode/self-referential network (DMN/SRN) anchors motivation by encoding the self-relevance of goals. High performance emerges only when these networks are in synchrony, dynamically integrating capacity, perception, and persistence [11–14].

This chapter argues that BCI-enabled adaptive systems are not merely new tools but a mechanism for finally operationalizing decades of educational psychology and human performance theory into real-time, actionable practice. This framework extends beyond optimizing performance to preventing failures before they occur, using predictive analytics to detect impending lapses in readiness, awareness, or motivation – and adapt the environment accordingly. In doing so, it shifts education from a reactive paradigm to a proactive, anticipatory model – one that incorporates not only cognitive readiness and situational awareness but also motivation/willpower as continuous, measurable, and trainable competencies.

The framework advanced in this chapter is intended for an audience working at the intersection of neuroscience, education, and human performance. It is written for researchers and technologists developing BCIs, for educators and trainers seeking proactive tools to sustain learning, and for practitioners in high-stakes fields – such as aerospace, defense, medicine, athletics, and corporate decision-making – who must preserve performance under pressure. Clinicians in neurorehabilitation, as well as policymakers and ethicists concerned with the responsible use of neurotechnology, may also find relevance in the protocols described. By bridging rigorous neuroscience with operational models, the chapter aims to serve both scientific and applied communities, making theory actionable across diverse domains.

This chapter is organized as follows. Section 2 reframes learning from reactive remediation to a proactive, anticipatory model and provides a Theory → Operations crosswalk that maps classic educational-psychology constructs (CR, SA, SRK, spacing/retrieval, cognitive load) to real-time loop actions, now expanded to include motivational alignment. Section 3 details the technology foundations – EEG and connectivity analytics – and defines continuous, measurable CR, SA, and motivational indices used for training and monitoring. Section 4 presents the integrated trait–state–motivation protocol (baseline traits, state detection, adaptive interventions, longitudinal tracking), introducing the predictive early warning layer,

anticipatory cueing with lockouts, and proactive outcome metrics (e.g., prevented-lapse rate and lead-time). Section 5 demonstrates applications across domains (education; aerospace/defense; medical/surgical training; neurorehabilitation; high-performance athletics; corporate decision-making). Section 6 explains how network connectivity links trait capacity to state vulnerability and willpower under load. Section 7 addresses ethical and implementation considerations (consent, data governance, transparency) and summarizes key limitations and assumptions. The authors conclude with a discussion and conclusion that synthesize implications and future research directions.

In this chapter, the author refers to two components: a trait-training component (e.g., NeuroCoach®) and a state monitoring/control component (e.g., IQity®/IQeeg®). The names are included only as illustrative examples; the underlying procedures and evaluation methods are fully vendor-agnostic. The protocols were developed and validated through extensive application of NeuroCoach® and IQity® systems across both 24-channel and 8-channel EEG montages, confirming that outcomes are not dependent on a particular hardware configuration. This ensures the framework can be implemented with comparable equipment and adapted flexibly across operational domains. Beyond technical validation, the framework reflects insights gained from years of applying these systems in clinical and non-clinical contexts – including rehabilitation, education, aerospace simulations, athletics, and organizational performance – providing the real-world grounding for the operational model advanced in this chapter.

2. From traditional to proactive learning models

Traditional approaches to learning and performance support in both educational and professional training contexts have been largely learner-centered but observational in nature. In this paradigm, educators and trainers monitor performance through tests, assignments, or on-the-job assessments, responding to errors, lapses, or reported difficulties after they occur [1, 2]. While this reactive model has historically been the norm, it carries several inherent limitations: delays between the onset of a difficulty and the intervention, reliance on subjective self-reports, and the absence of continuous monitoring during the learning process. As shown in **Figure 2**, this reactive sequence – observation → error → intervention → recovery – is contrasted with a proactive, BCI-enabled learning loop in **Figure 2**, which illustrates how early neural-state detection and predictive cueing allow intervention before overt performance breakdowns occur.

From an educational psychology standpoint, traditional approaches have long emphasized behavior- and skill-based assessments, such as standardized tests and

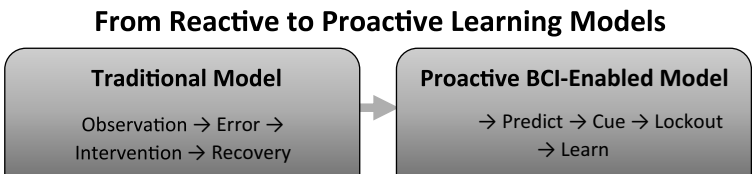


Figure 2.
The transition from reactive to proactive learning using BCI-based early warning and predictive cueing.

observable task performance [15]. These assessments focus on the *product* (end results like scores) of learning – scores and completed assignments – while giving less attention to the *process* of learning itself [16]. As a result, the learner's internal cognitive dynamics, such as attentional control, executive functioning, or cognitive load, often remain inferred rather than directly measured [17]. This becomes especially problematic when subtle cognitive disruptions – momentary lapses of attention, fluctuations in working memory, or mild overload – affect performance but leave no immediate behavioral trace, only surfacing later as visible errors or performance breakdowns [18, 19].

By contrast, proactive learning models aim to detect and respond to these disruptions before they manifest as performance breakdowns. With the integration of BCI systems, it becomes possible to monitor a learner's cognitive state in real time, adjusting task demands, pacing, or instructional strategy based on moment-to-moment neural data [7, 8]. For example, EEG-based workload indices can identify the early onset of cognitive fatigue, prompting the system to introduce a brief recovery period or shift to a less demanding activity to preserve performance capacity.

A key innovation of this proactive paradigm is the subdivision of learning into trait, state, and motivational/willpower modeling:

- Cognitive traits are stable, longer-term characteristics, such as baseline executive function, working memory span, or attentional control [2, 20]. These can be assessed through standardized neurocognitive testing and long-term EEG baseline measures.
- Cognitive states are transient, fluctuating conditions, such as current attentional engagement, stress level, or mental fatigue [10]. These are monitored in real-time using tools such as IQity® [8], which provide continuous state tracking and can trigger adaptive interventions during the learning process.
- Motivation/willpower reflect not only the persistence of effort despite fatigue, stress, or distraction but also the alignment of three underlying components: *intent* (direction), *motivation* (energy), and *capacity* (trait resources). When these are synchronized, willpower emerges as the sustained enactment of effort over time. Network neuroscience provides a basis for this framework: the default mode and self-referential networks (DMN/SRN) encode the self-relevance of goals (anchoring intent), the central executive network (CEN) regulates capacity and task control, and the salience network (SN) mobilizes motivational energy by dynamically allocating attention. Breakdowns in any one of these networks disrupt alignment, explaining why individuals with strong skills or intelligence may still underperform if intent is unclear, motivation is depleted, or capacity is compromised [11–14].

The shift to trait–state–motivation/willpower modeling creates a more precise adaptive framework: training can be customized to the learner's enduring capacities (trait-based personalization) while dynamically responding to momentary

fluctuations (state-based adaptation) and aligning tasks with motivational salience (motivation-based persistence).

This capability also enables the integration and operationalization of models that were once largely theoretical in education and training, including:

- **Cognitive readiness (CR):** the ability to rapidly adapt cognitive strategies to changing demands while maintaining performance under stress [2, 20].
- **Situational awareness (SA):** the perception, comprehension, and projection of elements in the environment relevant to decision-making [4].
- **Motivation/willpower (M):** the persistence to sustain effortful control, linked to self-referential processing and task relevance [12–14, 21–23].
- **Skills–rules–knowledge (SRK) model:** a human performance framework distinguishing between skill-based, rule-based, and knowledge-based behaviors [5].
- **Ebbinghaus forgetting curve:** describing the exponential loss of learned information over time without reinforcement [6].

Historically, these frameworks were applied qualitatively (e.g., design heuristics, after-action reviews). With BCI-enabled adaptive systems, each can now be measured in real time, allowing for closed-loop interventions that both train and sustain these competencies. In a proactive BCI-enabled loop, they become operational.

2.1 Theory–operations crosswalk: Translating cognitive learning into adaptive rules

Traditional learning theories describe what fosters durable learning but not how or when to intervene. In adaptive BCI systems, these theories become trigger rules – dynamic algorithms that connect detected neural or behavioral states to specific feedback actions. Each loop follows a “detect → interpret → intervene → verify” sequence, turning abstract learning principles into actionable control logic. These relationships are summarized in **Table 1**, which operationalizes major learning theories into adaptive trigger rules used by the closed-loop detect → interpret → intervene → verify architecture.

These mappings illustrate how long-standing cognitive theories can be expressed as real-time adaptive rules. Rather than post-session analysis or static difficulty scaling, interventions occur *within the learning episode itself*, sustaining cognitive readiness, situational awareness, and willpower simultaneously.

For example, in a university-based NASA analog habitat simulation applying the SRK model, EEG-based workload monitoring identified when expert operators shifted from skill-based to rule-based behavior during unexpected system anomalies – a transition often linked to reduced efficiency and increased error risk [24]. Proactive intervention at that moment, such as reducing secondary task load or providing targeted prompts, preserved both CR and SA in high-pressure conditions. With motivational indices added, the same system could also detect when persistence risked collapse, allowing interventions to preserve not just capacity and awareness, but also willpower.

Learning principle (theory)	Operational translation (adaptive rule)
Spacing and retrieval practice	Detect when alertness is moderate and error risk is low; trigger short review or retrieval probes to reinforce consolidation.
Desirable difficulties	Increase challenge only when cognitive readiness is stable and errors are bounded; pause escalation when early warning probability remains elevated.
Cognitive load management	When frontal θ or working-memory strain rises, simplify displays, externalize steps (checklists), and resequence tasks to offload cognitive load.
SRK targeting (skill-rule-knowledge)	Identify level of breakdown: skill lapse $\rightarrow$ attentional reset; rule breakdown $\rightarrow$ checklist or sequencing cue; knowledge impasse $\rightarrow$ strategy or modality change.
Deliberate practice	Set micro-goals, provide immediate corrective feedback linked to EEG/performance changes, and re-probe soon after to confirm stabilization.
Motivational alignment	Detect declining persistence or DMN/SRN instability; trigger reframing prompts, self-relevance cues, or value-linked resets to restore engagement.

Table 1.
Theory–operations crosswalk for adaptive learning.

This integration also opens the door to modeling and mitigating factors outside the traditional learning domain that can degrade network efficiency. Functional network connectivity analysis – mapping the dynamic interactions between brain regions during cognitive tasks – reveals how even high-IQ individuals can underperform if specific integrative hubs are compromised [25, 26]. Network science shows that disruptions in hub synchrony reduce flexibility under stress and impair performance [27, 28]. Importantly, these disruptions can also stem from non-cognitive sources, such as food allergies, chronic inflammation, or mild traumatic brain injury, all of which weaken network connectivity and resilience [29].

Thus, the proactive model is not merely about enhancing learning; it is about creating resilient cognitive systems capable of maintaining performance in the face of both internal and external challenges – including motivational/willpower alignment as a third, measurable, and trainable pillar of the Performance Triad.

3. Technology foundations for trait–state adaptive learning

The backbone of any BCI-enabled proactive learning model is the technology that can reliably measure and interpret cognitive states in real time, while also characterizing stable cognitive traits. This dual capability is essential because adaptive training depends on both accurate baseline profiling and dynamic, moment-to-moment monitoring.

Electroencephalography (EEG) has emerged as one of the most practical and informative modalities for monitoring cognitive processes due to its millisecond-level temporal resolution and portability [30, 31]. Advances in both low- and high-density dry-sensor EEG systems have enabled non-invasive and rapid setup, making continuous monitoring feasible not only in laboratory contexts but also in classrooms, flight simulators, and field operations [31–33]. For instance, dry electrode technologies now allow robust measurements of cognitive states in real-life operational settings [34]. Moreover, portable and multimodal EEG platforms are being actively developed to assess both baseline

cognitive traits – such as executive function efficiency and working memory integration – and transient state changes, including attentional lapses, cognitive overload, and stress-induced fluctuations [35–38].

Building on these advances, the authors' protocols were developed and validated through extensive application of both NeuroCoach® and IQity® platforms. Importantly, the procedures have been demonstrated across 24-channel and 8-channel EEG montages, confirming that their effectiveness does not depend on specific hardware configurations. This verification shows that the framework is vendor-agnostic and equipment-independent, ensuring that trait–state monitoring and adaptive training can be reliably implemented across diverse operational contexts using comparable EEG systems.

One of the most transformative aspects of neuroimaging technologies is their ability to quantify functional network connectivity (FNC) – the degree and pattern of synchronous activity between distinct brain regions during task performance [39]. Unlike traditional EEG analysis, which focuses on isolated regional activity, connectivity analysis captures the interplay across distributed neural circuits, highlighting how effectively the brain integrates information through specialized hubs [40]. For instance, strong coherence between the dorsolateral prefrontal cortex (DLPFC) and parietal regions has been shown to support executive control and rapid decision-making, processes central to CR [41, 42]. Conversely, disrupted connectivity within the salience and default mode networks has been linked to degraded SA and impaired performance in high-stakes environments [43, 44]. In the authors' applied work, they have demonstrated that reliable FNC measures can be computed with montages of 19 channels or more. When fewer channels are available, surface-proxy methods can provide usable estimates, with a minimum of 8 channels proving effective for training and monitoring. For higher-resolution evaluations and diagnostics, the authors recommend 19 or more channels.

The ability to track such connectivity in real time enables adaptive interventions precisely when they are needed. In a university-based NASA Habitat simulation applying the SRK model, EEG monitoring revealed that as task demands increased, certain operators experienced a decline in frontoparietal network efficiency, coinciding with a shift from skill-based to rule-based processing [24]. In practice, the adaptive system was designed to adjust task complexity and deliver visual prompts so operators could stay in a higher readiness state without triggering overload.

Beyond connectivity alone, the integration of trait–state modeling enables personalization that accounts not only for neural dynamics but also for environmental and medical influences. While functional network connectivity identifies *where* vulnerabilities occur, trait–state modeling specifies *when and in which networks* they are most likely to emerge. For example, individuals with strong baseline cognitive traits may still exhibit state-based breakdowns during prolonged or complex tasks due to vulnerabilities in the cognitive control network [45, 46]. Crucially, emerging evidence shows that systemic inflammation and related medical or lifestyle factors can impair the stability of neural synchrony by weakening sub-connections within critical hubs, thereby producing variable performance under different cognitive loads [47–50]. Such effects help explain why individuals with high measured IQ sometimes underperform under stress or fatigue, as inflammatory processes reduce network resilience and adaptability [51, 52]. By identifying these trait–state–environment interactions early, adaptive training protocols can be tailored both to strengthen target networks and to mitigate environmental

contributors – such as sleep disruption, chronic inflammation, or prior concussions – that exacerbate cognitive fatigue and degrade performance [53].

From an operational standpoint, this capacity transforms cognitive readiness and situational awareness from abstract constructs into quantifiable, trainable skills. Rather than relying solely on retrospective reports or after-action reviews, the system provides continuous state telemetry – a live stream of cognitive metrics that can be aligned with task events to identify precise triggers of performance degradation. Over time, this produces a personalized “cognitive fingerprint” for each learner, mapping how trait capacities and state fluctuations interact across different task contexts [7, 8, 24].

In sum, these sensing and analytics capabilities enable a closed-loop cognitive environment: the same EEG/connectivity features that describe the learner’s state also drive adaptation and logging. To make this operational rather than descriptive, the authors define two continuous measures – one for cognitive readiness (CR) and one for situational awareness (SA) – computed from the features already described in this section. These indices serve as the loop’s “state variables” and connect Section 3’s technology to the anticipatory control in Section 4.

3.1 Cognitive readiness (CR) index (0–100)

CR quantifies the learner’s moment-to-moment capacity to sustain task performance or learning. It is computed per session and trended longitudinally from the same features described above (e.g., frontoparietal β coherence, frontal midline θ , DMN α suppression). By combining electrophysiological indices with temporal stability measures, CR reflects both immediate readiness and longitudinal resilience.

- **Primary proxies:** (i) *time in the ready band*. Proportion of task time with individual-specific β – θ balance within target ranges, emphasizing frontoparietal coherence (CEN–parietal network coupling) and stable DMN α suppression during externally oriented attention; (ii) *stability*. Low drift/variance across time windows, indexed by consistent PFC–parietal β coupling and reduced cross-network “flicker” (rapid, unproductive switching between DMN and CEN); (iii) *recovery time*. Seconds to return to the ready band following a micro-intervention or overload, with anterior cingulate θ rebound and insula–ACC salience response as neural markers of recovery capacity; and (iv) *sustained alertness*. Tonic mid-band activity (alpha/theta ratios over frontal and parietal leads) as an index of physiological readiness for continuous effort.
- **Reporting:** Composite scaled 0–100 with weekly Δ CR and a minimal Detectable Change threshold to differentiate noise from true gains. Stratify by task context and tonic alertness band. CR trends are tracked longitudinally to illustrate durable capacity building.
- **Use in the loop:** Difficulty increases are gated to periods of stable CR. If CR deteriorates – indicated by rising variance, prolonged recovery times, or reduced tonic alertness – the system inserts a micro-recovery drill. CR indices are displayed to the learner to reinforce self-regulation strategies and to demonstrate that readiness is not static but trainable.

3.2 Situational awareness (SA) proxies (continuous)

SA is estimated via unobtrusive proxies that can run in the background and be spot-checked without disrupting flow. These combine behavioral response metrics with neural indicators of perception–comprehension–projection, the three canonical layers of SA.

- **Primary proxies:** (i) *DMN intrusion reduction in task-critical epochs.* Reduced medial prefrontal and posterior cingulate α coherence during action phases indicates effective suppression of internally oriented thought and better external situational monitoring. (ii) *First action after a cue (latency and accuracy).* Early sensory–motor coupling, indexed by parietal P300 amplitude and frontoparietal β synchronization, reflects rapid cue recognition and translation into action. (iii) *Brief freeze/probe checks at natural pauses.* Performance accuracy and latency in perception–comprehension–projection probes, combined with transient connectivity shifts between the dorsal attention network (DAN) and salience network (SN), serve as neurocognitive markers of situational model updating. (iv) *Error-sensitive adjustments.* ACC–insula activity patterns, reflecting salience detection and error reallocation, predict whether awareness is being actively maintained under dynamic conditions.
- **Reporting:** Prefer separate proxy readouts (optionally, a simple composite index for dashboards). Summarize by task phase and tonic band; track weekly deltas to show that SA is trainable (faster first actions, + fewer DMN intrusions, and stable probe accuracy). Log cue→action pairs so analyses target the first post-cue operation, where effects are expected to concentrate.
- **Use in the loop:** If SA proxies deteriorate – e.g., rising DMN intrusion with slower first actions – apply anticipatory adjustments (declutter, re-prioritize steps, short reset) before increasing task complexity.

3.3 Motivation/willpower proxies (m) (continuous)

Motivation/Willpower is operationalized here not as an isolated trait but as the emergent enactment of three aligned elements: intent (clarity of goal), motivational drive (affective energy toward the goal), and cognitive capacity (resources sufficient to sustain execution). To integrate this construct into the closed-loop system, proxies are derived from both behavioral persistence and neural markers of self-relevance.

- **Primary proxies:** (i) *effort duration before disengagement.* Measured as cumulative task time sustained prior to lapse or withdrawal, with concurrent frontal midline θ (ACC) and dorsolateral prefrontal β activity as indicators of top–down control over sustained effort; (ii) *adaptive re-engagement after micro-failures:* quantified by latency and frequency of resuming task engagement after errors or overload, indexed by salience-driven switching (anterior insula + ACC co-activation) and P300 amplitude recovery as markers of error recognition and motivational reallocation; (iii) *self-relevance dynamics.* Tracked through DMN/self-referential network (medial PFC, PCC)

co-activation with the central executive network (DLPFC, parietal cortex) and salience network (insula/ACC) during task-anchored goals. Greater synchrony reflects internalization of goals as self-relevant, supporting persistence under increasing demand; (iv) *frustration tolerance and reward sensitivity*: indexed by ventral striatal engagement (δ/β ratios) during delayed reward tasks and reduced amygdala hyperactivation under stress probes; persistence in these conditions marks the neural substrate of willpower as sustained capacity for goal pursuit.

- **Reporting:** Scaled 0–100, stratified by task type and difficulty band. Weekly deltas are emphasized to distinguish transient fatigue from more durable motivational changes. Minimal Detectable Change thresholds are calculated to validate persistence trends against noise.
- **Use in the loop:** If motivation/willpower proxies deteriorate – e.g., shortening of effort duration or reduced re-engagement – the system deploys reinforcement protocols: self-relevance priming cues, scaffolding toward micro-successes, or adaptive difficulty lowering to preserve task engagement. Longitudinal M trends are fed back to the learner as a persistence gauge, reinforcing the principle that willpower is itself a trainable state within the triad.

Together, CR, SA, and M form the three continuous state variables of the Performance Triad. Each is computed from the same EEG/connectivity features and behavioral markers described above, ensuring they are not abstract constructs but operational indices. In practice, CR captures the learner’s moment-to-moment neurocognitive capacity; SA reflects the suppression of irrelevant internal activity and the fidelity of perception–comprehension–projection; and M represents the persistence of goal-directed effort when intent, motivational drive, and cognitive capacity align. These three indices drive the predictive layer introduced in Section 4: (i) sensing of EEG and task signals, (ii) short time-horizon prediction of lapse risk, (iii) anticipatory cueing with mid-band tonic alertness thresholds and two-hit confirmation, (iv) single-shot interventions with short lockouts, and (v) evaluation using Prevented-Lapse Rate, lead-time, intervention yield, and false-alarm cost. In this way, the closed-loop framework does not merely describe CR, SA, and M but renders them measurable, trainable, and adaptive in real time, with each leg of the triad reinforcing the others.

4. Protocol design for proactive learning

The authors have found that designing a protocol that effectively integrates trait and state adaptive learning requires more than simply placing a BCI device on



Figure 3.
Methodology roadmap for trait–state adaptive learning: a four-phase roadmap linking baseline traits, state monitoring, adaptive feedback, and longitudinal growth.

a learner's head. It demands a structured, multi-phase approach that combines baseline cognitive profiling, real-time state monitoring, adaptive feedback, and longitudinal tracking, as illustrated in the methodology roadmap shown in **Figure 3**. This design must also directly operationalize established learning and performance models – such as CR, SA, the SRK framework, and the Ebbinghaus forgetting curve – so that they become actionable in day-to-day instruction [4–8].

4.1 Phase 1: Trait baseline assessment – “*know the learner*”

The first stage involves establishing a trait profile for the learner. In the NeuroCoach[®] framework, this begins with EEG-based connectivity assessments across key neural networks associated with executive function, working memory, emotional regulation, and cognitive flexibility [9]. These networks are mapped against normative databases to identify strengths and vulnerabilities [54]. For example, reduced connectivity between the anterior cingulate cortex (ACC) and the dorsolateral prefrontal cortex (DLPFC) might indicate a reduced capacity for sustained attention – a trait limitation that could hinder both CR and higher levels of SA in complex environments.

This phase also incorporates cognitive-behavioral and psychometric measures to cross-validate the EEG findings. The SRK model is useful here, as it helps classify whether a learner's dominant problem-solving approach is skill-based, rule-based, or knowledge-based [5]. If EEG patterns suggest that network efficiency breaks down during tasks requiring fluid switching between these modes, the baseline profile will document this as a potential adaptation target in later phases.

Trait mapping is aligned with the SRK framework to identify the learner's default mode (skill/rule/knowledge) under low stress and susceptibility to regression under load; this alignment guides later intervention targets. A baseline connectivity screen can reveal, for example, strong frontoparietal integration (supporting reasoning and requiring sustained planfulness – that is, deliberate foresight and organized goal pursuit) but weaker temporoparietal theta synchrony (auditory-verbal working memory), which informs initial task design [55, 56].

Note: The protocol described here is a generalizable design pattern intended for education, clinical training, and operational settings; examples are illustrative and do not imply completed controlled trials in a single domain. However, they were derived from both the authors' clinical and non-clinical work over the years in various operational settings.

4.2 Phase 2: State detection and real-time monitoring – “*stay ahead of the slip*”

Once the trait profile is established, the system takes on a central role by continuously monitoring state-level fluctuations during learning activities [7–9]. This involves tracking EEG features such as phase synchrony, coherence, and power spectral density across targeted frequency bands known to correlate with attention, working memory load, and stress responses [57–60].

Operational example: In simulator, classroom, or clinical training environments using the SRK framework, learners who show abrupt reductions in alpha-phase coherence between frontal and parietal regions during complex tasks often exhibit downstream situational-awareness loss. The adaptive loop detects these shifts and

delivers *micro-interventions* – such as workload redistribution or augmented visual cues – to stabilize network efficiency before behavioral decline occurs.

4.2.1 Thresholds and drift guards

Each learner's state thresholds are individualized relative to baseline – for example, ± 1.5 z deviation in frontoparietal β coherence, frontal θ , or DMN α coherence. Sustained deviation across N consecutive windows triggers either a micro-intervention or a temporary pacing adjustment before observable performance loss. This ensures early stabilization rather than late correction.

4.2.2 Predictive early warning (3–10 s time horizon)

To make the loop anticipatory rather than merely reactive, the authors compute a short-horizon early-warning index (EWI) that forecasts the probability of a performance lapse (e.g., error, timeout, critical deviation) 3–10 seconds ahead. The EWI is updated on rolling windows of recent data (e.g., last 5–10 s), sampled every 250–500 ms, using trends in both neural and behavioral features – for example, frontoparietal β -coherence drift, frontal θ rise, DMN- α coherence drop, and reaction-time variance/micro-lags. The model outputs a probability P_{lapse} that a lapse will occur within the next few seconds.

4.2.3 Dispatch policy (pre-emptive, not reactive)

- Fire a micro-intervention (e.g., 20–30 seconds attentional reset, declutter secondary load, brief pacing reduction) only if:
 - Tonic alertness is in the mid-zone (learner-specific band), and,
 - P_{lapse} exceeds the threshold in ≥ 2 consecutive updates (hysteresis to curb false alarms).
- After any dispatch, apply a 1–2 seconds lockout before considering another alert.
- Log event metadata – triggered feature(s), warning-to-event lead time, and intervention type – for evaluation.

4.2.4 Safeguards

- Cap cue frequency (e.g., ≤ 2 –3 per minute) to avoid habituation.
- If accuracy drops post-cue (speed–accuracy trade-off), extend the lockout and temporarily reduce task demand.
- When high P_{lapse} does not lead to errors (possible over-sensitivity), bias toward subtle adjustments (pacing or sequencing) rather than providing further cues.

4.2.5 Evaluation (reported in outcomes)

- Prevented-lapse rate (PLR): lapses avoided after early-warning interventions.
- Lead-time distribution (median, IQR).
- Intervention yield: lapses avoided per 100 interventions.

4.2.6 Applied examples

In both flight-simulation and educational contexts, similar dynamics apply: when frontal θ rises and frontoparietal β coherence declines over ~ 6 seconds, the EWI predicts a lapse window. A pre-emptive cue – such as temporary load reduction or pacing adjustment – can avert performance decline. This event counts toward PLR and demonstrates how predictive BCI monitoring turns state awareness into actionable prevention rather than after-the-fact correction.

4.3 Phase 3: Adaptive intervention design – “coach the moment”

The adaptive intervention phase links state detection to actionable feedback. Here, the goal is to create a closed-loop adaptive learning environment in which task difficulty, pacing, and instructional modality can be modulated moment-to-moment based on the learner’s neurocognitive state. For example, using a state monitoring system that detects sustained frontal theta elevation alongside reduced frontoparietal coherence – a signature of cognitive fatigue – the system might insert a brief brain wake-up exercise based on a cognitive resilience drill targeting the implicated network or suggest that the user take a brief break, as the authors do with the IQity[®] Performance System [9].

Integrating the Ebbinghaus Forgetting Curve into this loop allows for proactive reinforcement scheduling. Rather than relying on fixed intervals, review sessions are triggered dynamically when state monitoring detects declines in task-relevant network efficiency, thus optimizing memory consolidation before recall degradation occurs.

Anticipatory cueing and lockouts. To make cueing proactive (not merely reactive), phase-dependent cues are timed relative to predicted lapse windows from the early-warning logic in 4.2. Below are several lessons the authors learned to integrate during their university NASA Habitat simulations.

- When to cue: Issue a cue only if (1) tonic alertness is in the learner’s mid-band and (2) the EWI exceeds the threshold in ≥ 2 consecutive updates. Aim for the critical sub-action to occur within the phasic window (≈ 100 – 1500 ms) after the cue.
- One cue per action. Deliver a single cue for the intended operation; do not stack cues before the first action is executed.
- Lockout: Apply a 1–1.5 second lockout after each cue (or until the first action completes), preventing redundant alerts and interference.

- If accuracy dips post-cue, temporarily lengthen the lockout and down-shift task difficulty and/or declutter secondary load; resume escalation only after stability returns.
- Rate limiting: Cap cue frequency (e.g., $\leq 2-3$ pre-emptive cues per minute) and fall back to non-cue adjustments (pacing, sequencing) if high-risk persists without behavioral benefit.
- Logging and analysis. For each cue, log lead-time (warning→action), the feature bundle that triggered the EWI, and the resulting outcome. Analyze effects on the *first action after the cue* (latency and accuracy) and by *tonic band* (low/mid/high) to verify the expected concentration of benefits.

4.4 Phase 4: Longitudinal trait-state tracking – “map the growth”

Over weeks and months, the protocol can generate a detailed “cognitive performance map” for each learner, showing how their state dynamics evolve relative to trait capacities. This long-term dataset enables a trait-state convergence analysis, in which persistent vulnerabilities can be targeted for structural remediation, while transient fluctuations are addressed with just-in-time strategies.

For example, the authors have observed in their clinical setting that a high-IQ engineering student may perform well in low-pressure contexts but underperform when deadlines compress. Network connectivity analysis may reveal that, under stress, the dorsolateral prefrontal cortex (DLPFC) temporarily decouples from parietal and salience hubs, impairing working-memory prioritization. Adaptive training can then focus on (i) strengthening this connectivity pattern and (ii) teaching self-regulation techniques to preserve network stability under time constraints [61, 62].

4.5 Evaluation design summary – “prove the gain”

To verify that the loop is anticipatory (not merely reactive), the authors compare sessions with early-warning OFF (reactive only) versus early-warning ON (pre-emptive cues under the Section 4 policy). Designs: AB/ABA N-of-1 for individual causality and a counterbalanced crossover cohort for group effects. Primary, vendor-agnostic outcomes: Prevented-Lapse Rate (PLR), lead-time (warning→event), intervention yield (lapses avoided per 100 interventions), false-alarm cost, and first-action after cue (latency/accuracy). All cues observe guardrails (one cue per action; 1–1.5 s lockout; $\leq 2-3$ cues/min; tonic mid-band gate). Results are reported by task and tonic band, with sensitivity checks across state-model K.

In addition to traditional CR and SA metrics, evaluation protocols should explicitly incorporate motivational persistence outcomes. These may include:

- Time-on-task under load, as a measure of sustained effort.
- Recovery latency, or the time required to re-engage after cognitive fatigue, refers to the duration needed to regain focus and mental clarity following periods of intense mental exertion.

- Dropout prevention indices capture whether motivational interventions reduce disengagement in longer learning modules.
- Self-reported alignment scores assess whether learners perceive tasks as relevant to their personal goals or values.

Integrating these persistence-focused outcomes ensures that evaluation captures all three legs of the Performance Triad, confirming that BCI-enabled systems not only prepare learners cognitively and situationally, but also sustain their motivation to apply effort over time.

5. Applications across domains

The examples that follow are drawn from three sources: (i) projects and prototypes conducted by the authors (e.g., SRK-informed flight-simulation studies, education pilots), (ii) illustrative scenarios designed to show how the control policy generalizes to new settings, and (iii) findings from the broader neuroergonomics and cognitive neuroscience literature. This chapter presents them in a consistent format to highlight the universality of the adaptive loop, but readers should note that not every scenario represents an empirical trial conducted by the authors’ team. Although implementation details vary by context, all applications described below rely on the same sense → predict → cue → lockout → evaluate architecture, with domain-specific tuning rather than structural change, as illustrated in **Figure 4**.

A shared loop, tuned to context.

The applications that follow all implement the same control policy introduced in Sections 3–4: *sense* → *predict* (*short-horizon risk*) → *gate* (*tonic mid-band with two-hit confirmation*) → *cue one pre-emptive micro-intervention* → *lockout* (1–1.5 s) → *evaluate*. Evaluation is consistent across domains – prevented-lapse rate (PLR), lead-time, intervention yield, false-alarm cost, and the first action after the cue – so improvements are comparable and auditable.

What varies by domain?

What changes from one setting to another is not the loop but its “knobs”:

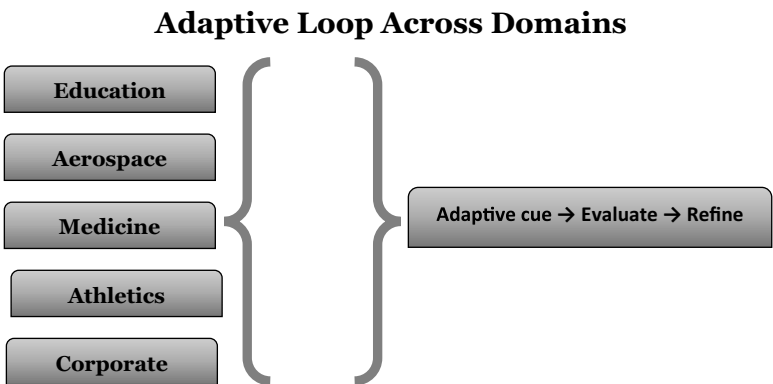


Figure 4. Adaptive loop across domains: all domains apply the same sense–predict–cue–lockout–evaluate loop, tuned for contextual demands through adaptive frameworks.

- The features monitored (EEG/connectivity plus task, IMU, or UX signals);
- The thresholds and guards (how much drift, for how long, and in which task phases);
- The micro-intervention library (what is acceptable and effective in that context); and
- The success criteria and constraints (what counts as “good” and what must not be disrupted – e.g., instructional flow, mission safety, sterility, competition rules, meeting etiquette).

How to read each subsection?

Each domain write-up states (i) the pre-lapse signatures it watches for, (ii) the dispatch policy (still vendor-agnostic early warning with gating/lockouts), (iii) the allowed interventions and why they fit that setting, and (iv) the outcomes used to judge effect. This keeps the architecture consistent while making the tuning choices explicit.

5.1 Education: From reactive to proactive learning support

In classrooms and learning centers utilizing this approach, the old model intervenes only after errors occur. A trait-state protocol runs continuously, estimating learning readiness and near-term lapse risk. When pre-lapse drift appears – posterior-parietal ↔ prefrontal β -coherence trending down for $\geq N$ windows, rising frontal θ , RT variance creeping up – the EWI crosses the threshold in two consecutive updates and triggers one pre-emptive micro-intervention (20–30 s): declutter the step sequence, initiate a brief attentional reset, lower pacing, or swap to a worked example before resuming. Guardrails are applied: one cue per action, 1–1.5 s lockout, ≤ 2 –3 cues/min; difficulty upshifts occur only when CR is stable. Spacing/retrieval is state-gated (fire when risk is low, tonic mid-band) rather than clocked [8, 9, 63–67]. The system measures what it prevents – PLR, lead-time, yield, false-alarm cost – and demonstrates immediate effects on the first action after the cue (latency/accuracy) alongside weekly CR/SA trends.

5.2 Aerospace and defense: Maintaining CR in high-stakes environments

In the university-based NASA analog habitat SRK-informed simulator trials, the loop estimates near-term situational awareness (SA) degradation before it becomes behaviorally visible. When pre-lapse drift emerges – frontoparietal β -coherence trending downward, frontal θ rising, combined with short-run increases in checklist execution time, mode flips, or reaction-time variance – a vendor-agnostic EWI signals elevated lapse risk. In such contexts, a single pre-emptive micro-intervention may be issued: re-prioritize cockpit displays by decluttering non-critical symbology, provide a brief scan/confirm prompt, redistribute workload across crew members, or temporarily defer non-urgent communications for 20–30 seconds. Guardrails ensure operational discipline: only one cue per action, 1–1.5 seconds lockout, and no more than 2–3 cues per minute, with interventions gated to mid-band tonic alertness. SRK regressions are addressed explicitly: if behavior

collapses knowledge→rule, a strategy-switch/context reminder is provided; if rule→skill, the active rule/checklist is surfaced to prevent slips [4, 5, 8, 67–69]. Modern EEG and neuroergonomics studies confirm that these drift patterns – declines in β -coherence and rises in frontal θ – are predictive of degraded situational awareness across high-stakes environments, including air traffic control, piloting, and military command-and-control tasks [68, 69].

5.3 Medical and surgical training: Reducing error through network stability

For example, in a hypothetical medical settings scenario, the loop forecasts near-term error risk in phases like clamp/dissect/suture. When pre-lapse signatures emerge – frontal θ rising with salience–executive decoupling (reduced CEN–SN coherence), growing tool-path jerk, small step-transition delays – the EWI triggers one pre-emptive micro-intervention (20–30 s): surface the next checklist step, declutter non-critical visuals, down-shift tempo, or insert a short breath/focus reset. Guardrails: one cue, 1–1.5 s lockout, ≤ 2 –3 cues/min; cues gated to mid-band tonic alertness. Effectiveness is measured by PLR, lead-time, yield, false-alarm cost, and fast task metrics on the first action after the cue (cut-path error, time-to-target, suture accuracy) [70, 71].

5.4 High-performance athletics: Bridging physical and cognitive readiness

With previous athletic studies, this work has demonstrated that the loop can forecast near-term timing errors. When pre-lapse signatures emerge – premotor–parietal β desynchronization, rising frontal θ , and small spikes in control-input jitter or IMU micro-tremor – the EWI triggers one pre-emptive micro-intervention (20–30 s): visual re-centering on reference marks, breath-cadence reset, brief radio quiet, or temporary widening of the pacing window. Guardrails ensure discipline: one cue, 1–1.5 s lockout, ≤ 2 –3 cues/min, mid-band tonic gate. Effectiveness is tracked through PLR, lead-time, yield, false-alarm cost, and sport-specific metrics such as missed apex/brake points, lap-variance, and reaction time off lights [72–75].

5.5 Corporate decision-making: Managing cognitive load in time-critical contexts

In information-dense meetings, micro-forgetting and prioritization slow when hippocampal –prefrontal/theta-linked encoding proxies weaken. At state thresholds, the loop triggers one short reset: summarize-and-park, re-order the agenda, or a 60–90 s breathing/quiet focus. Guardrails apply as above. Effectiveness is measured by PLR, lead-time, yield, false-alarm cost, and decision-quality proxies such as recall accuracy on key numbers, timeliness of decisions, and reduced re-work rate [76–79].

5.6 Cross-domain insights

Across empirical projects, published studies, and illustrative scenarios, several principles converge and emerge, highlighting the universality of the adaptive loop and the Performance Triad:

1. Network vulnerabilities predict performance failures even in high-ability individuals. Whether in a classroom, cockpit, operating room, racetrack, or boardroom, lapses arise not from a lack of skill or intelligence, but from transient disruptions in network coherence. Monitoring connectivity in real time allows these vulnerabilities to be detected before they surface behaviorally.
2. Real-time state monitoring transforms remediation into anticipatory stabilization. Instead of waiting for errors or disengagement, the system shifts support earlier in the timeline – stabilizing networks before performance deteriorates. This makes interventions less disruptive and more cost-effective.
3. Trait–state–motivation alignment is trainable. Just as endurance can be conditioned in athletics, network stability and motivational persistence can be strengthened through deliberate practice. Over time, learners and professionals can be trained to resist degradation under stress, fatigue, or overload.
4. The Performance Triad provides a universal lens. CR, SA, and motivation/ willpower (M) manifest differently across domains, but their neural underpinnings map consistently to the central executive network, salience network, and default mode/self-referential network. This makes the triad a transferable framework for both research and applied practice.
5. Educational and ethical implications cut across settings. For students, real-time monitoring can sustain persistence in challenging STEM tasks. For professionals, it can prevent costly errors in high-stakes work. In both cases, ethical safeguards are essential to protect privacy, autonomy, and equity of access.

Taken together, these insights show that BCI-enabled adaptive systems are not domain-specific tools but a generalizable architecture for resilient performance. They unify technical training, educational persistence, and ethical responsibility under a single model of proactive neuroadaptive support.

6. Network connectivity as a predictor of performance and willpower

One of the most persistent puzzles in applied neuroscience is why some individuals with high baseline intelligence or advanced skill underperform in real-world high-stakes situations. This phenomenon is not new – decades of research have noted the disparity between potential and actualized performance under varying conditions [80]. The emerging consensus is that while IQ and domain-specific skills capture trait capacity, they fail to account for the dynamic, moment-to-moment neural states that enable or impair execution of that capacity in context [81–83]. Modern neuroergonomics research further shows that performance often follows the Yerkes–Dodson law: both under- and over-arousal can destabilize frontoparietal control and salience–executive coupling networks, reducing neural efficiency and degrading task integration even in high-ability individuals [84, 85]. This effect has been demonstrated in aviation and defense operations, where elevated stress

narrows attentional scope and degrades situational awareness, and in surgical settings, where cognitive overload impairs decision-making despite high technical skill. Together, these findings suggest that the key to resilient high-stakes performance lies not only in developing trait capacity but in monitoring and stabilizing neural state dynamics in real time.

The network connectivity framework addresses this gap by shifting focus from static measures of ability to the integrity and adaptability of the functional brain networks that support performance. In this model, cognitive and behavioral outcomes are the result of coordinated interactions among multiple large-scale networks – including the CEN, DMN, SN, and various sensory-motor integration hubs [86]. When these networks are in stable synchrony, the brain can fluidly shift between planning, execution, and monitoring. When they become unstable – due to stress, fatigue, emotional overload, or physiological disruption – performance drops sharply, even in individuals with exceptional raw ability [61].

6.1 Why willpower (intent–motivation–capacity alignment) falters under load?

The concept of “willpower” in performance contexts overlaps with self-regulation, resilience, and executive persistence. Within the intent–motivation–capacity (IMC) alignment model, willpower is understood as the emergent enactment that arises when (i) intent is clearly defined and anchored, (ii) motivational energy is available to pursue that intent, and (iii) sufficient cognitive capacity exists to execute the goal under stress. Breakdowns in willpower occur when any one of these three components is misaligned.

Neurophysiologically, sustained willpower requires the coordinated interplay of the CEN, the SN, and the DMN/SRN. The CEN, especially dorsolateral prefrontal cortex regions, provides the working capacity and executive control necessary to maintain task goals. The SN, centered in the anterior cingulate and insula, regulates switching between networks and prioritizes whether attention is allocated toward task-directed or internally directed processing. Once characterized as “task-negative,” the default mode network – particularly its midline hubs (mPFC, PCC) – is now recognized as central to self-referential and goal-relevance processing, not just rest-state activity [11, 12].

When goal intent is framed as self-relevant, midline DMN (mPFC/PCC) signals of self-referential valuation increase, which is associated with greater persistence under pressure. Disengagement tends to occur when CEN–DMN coupling weakens or SN-mediated switching fails to align internal goals with external task demands. Likewise, when capacity constraints (working memory, attentional bandwidth, or physiological energy) are exceeded, intent and motivation cannot reliably translate into effective control. Thus, willpower typically falters not due to a single deficit but from a breakdown in the alignment of intent (self-relevance/valuation), motivation (effort allocation), and capacity (available control resources) across DMN–SN–CEN interactions.

For example, in the university NASA analog habitat mission, it was found that a pilot may demonstrate exceptional planning and problem-solving during low-stress simulations. However, during an extended EVA simulation under time pressure, state monitoring analysis may reveal declining CEN–SN coherence accompanied by altered DMN dynamics. If the task no longer resonates with the pilot’s self-concept or intrinsic motivation, DMN instability may manifest as

attentional disengagement and reduced persistence [12–14]. Although the pilot may still be consciously “trying,” the neural architecture required to sustain effortful control is no longer optimally aligned. This highlights the importance of motivation: willpower is strongest when CEN-driven effortful control is reinforced by DMN/SRN encoding of personal relevance. State monitoring protocols can, therefore, integrate targeted cognitive readiness drills and motivational reframing to restore network stability and operational willpower in real time [8].

6.2 Ego depletion, motivation, and network neuroscience

The longstanding debate on ego depletion illustrates why willpower would benefit from being reframed through network neuroscience. The classic resource model suggested that willpower operates like a limited muscle: exertion depletes a finite store of self-control, making persistence harder [21]. However, replication crises and meta-analyses have cast doubt on this resource account. More recent theories argue that willpower failures reflect shifts in motivation and attention rather than depletion per se, which is more in alignment with the IMC model of willpower [22, 23].

Network neuroscience provides a mechanistic bridge: the CEN can maintain control, but only if the DMN/SRN encodes the task as motivationally relevant. When tasks cease to feel self-relevant, the SN reallocates resources away from CEN persistence and toward internally oriented or alternative goals. In this framework, ego depletion is not a loss of energy but a recalibration of salience: individuals disengage because the neural circuitry supporting willpower no longer encodes the task as worth the effort.

This model explains why motivational reframing – tying tasks to self-identity, values, or meaningful goals – can restore persistence. It also highlights why temperament matters: individuals with stronger self-referential orientations may show greater resilience when tasks align with personal identity, while those with other- or context-referential orientations may disengage unless external motivations (e.g., team identity, mission framing) sustain DMN/SRN involvement.

Applied example link: Returning to the university-based NASA pilot scenario in Section 6.1, ego depletion in this context should not be viewed as a simple exhaustion of control resources. Instead, it can be understood as a motivational shift: as the EVA simulation becomes prolonged and stressful, the pilot’s SRN may fail to encode the task as sufficiently self-relevant. This disengagement cascades into CEN–SN instability, producing lapses in judgment and persistence. Thus, operational willpower is preserved not by resisting depletion but by ensuring ongoing motivational alignment through targeted interventions.

6.3 Physiological and environmental insults to network integrity

Network stability is also vulnerable to subtle but chronic physiological insults – factors often overlooked in performance training. Food sensitivities and diet-driven inflammation, for instance, can trigger low-grade systemic immune activation that alters neural signaling efficiency and disrupts large-scale brain network dynamics [87, 88]. In such cases, even a highly intelligent learner may struggle with sustained focus or complex integration tasks, not because of cognitive

incapacity but because inflamed neural pathways reduce synchronization bandwidth between critical cortical hubs.

Similarly, metabolic dysregulation, dehydration, or sleep deprivation can selectively impair hubs such as the anterior cingulate cortex, reducing error monitoring and adaptive decision-making [89]. IQeeg[®] connectivity mapping can detect these changes in network stability before behavioral symptoms become evident, prompting early intervention – whether through medical evaluation, nutritional adjustment, or targeted cognitive re-engagement exercises.

6.4 Linking network vulnerability to the trait–state framework

Understanding performance failures through the lens of network connectivity reframes the trait–state distinction. Traits – such as working memory capacity, reasoning ability, or verbal fluency – represent the structural potential of the system, much like a high-performance engine. States – reflected in real-time network dynamics – are the operational condition of that engine under varying weather, terrain, and load contexts.

Temperament adds a third layer: individuals differ in how strongly their SRN encodes *self-referential vs. other-referential* goals. A learner with a temperamentally self-focused orientation may sustain willpower more effectively if tasks are framed as self-relevant. Conversely, individuals with stronger other- or context-focused orientations may require alignment with external motivations – such as team cohesion or mission objectives – to maintain persistence. This interplay of trait capacity, state dynamics, and temperament-driven motivation explains why equally skilled individuals diverge in real-world resilience.

The adaptive BCI protocol, operationalized in state monitoring, enables the detection of these conditions as they emerge, applying corrective training or motivational reframing in real time [8].

6.5 Case example: High-IQ underperformance in a space analog task

During a 30-day high-fidelity Mars mission simulation, one crew member – an engineer with exceptional baseline intelligence and strong technical skills – was observed to disengage during multi-system failure drills. Traditional performance metrics suggested a motivational lapse. However, IQeeg[®] analysis revealed that the disengagement coincided with transient but repeated breakdowns in CEN–SN connectivity, along with elevated limbic reactivity. Post-mission interviews confirmed that the crew member experienced intrusive physical discomfort from an undiagnosed gluten sensitivity, which was later confirmed through medical testing.

From a network perspective, this case illustrates more than a physiological disruption: it also reflects a motivational misalignment. The engineer reported that prolonged discomfort undermined their sense of self-efficacy and personal relevance within the mission, weakening SRN engagement. As the task ceased to feel aligned with self-identity, willpower faltered despite strong technical ability. Once identified, dietary adjustments combined with targeted NeuroCoach[®] network regulation training restored both physiological stability and motivational alignment. In subsequent analog trials, performance scores and network synchrony improved, illustrating that operational willpower depends on both stable connectivity and the continuous encoding of task relevance within self-referential circuits [8].

6.6 Synthesis: Network dynamics, temperament, and motivational alignment

Taken together, these findings suggest that willpower is best understood as an emergent property of network synchrony modulated by intent, motivation, and network capacity. The CEN provides the executive machinery, but persistence falters when the SN fails to allocate resources toward goals encoded as self-relevant by the DMN/SRN. Physiological insults, fatigue, and stress destabilize this synchrony, while temperament shapes whether individuals default to self-referential, other-referential, or context-driven motivational anchors. High-stakes performance resilience, therefore, cannot be explained by trait ability alone; it depends on aligning task demands with motivational salience, stabilizing network dynamics in real time, and embedding interventions that maintain or restore the felt relevance of effort. Framed through the Performance Triad, willpower is the emergent capacity that results when intent, motivation, and resources are coherently integrated.

6.7 Practical applications of willpower

To translate this framework into practice, it was found that operational environments must treat willpower as a dynamic system of motivation and network synchrony, not merely as cognitive endurance. To this end, several application domains emerge:

1. *Training for motivational alignment:* Beyond technical drills, readiness programs should incorporate strategies that help individuals reframe tasks as self-relevant (e.g., linking procedures to mission identity, personal values, or long-term goals). These drills strengthen SRN engagement and buffer against motivational disengagement.
2. *Team- and culture-based scaffolding:* For individuals with stronger other- or context-referential orientations, persistence can be enhanced through team cohesion and organizational culture cues. Shared mission identity, peer accountability, and collective narratives serve as external anchors that sustain DMN/SRN engagement.
3. *Real-Time monitoring and intervention:* Wearable EEG, fNIRS, and physiological sensors can detect early markers of CEN–SN breakdown or DMN instability. These signals can trigger adaptive interventions such as attentional reset drills, workload redistribution, or guided breathing protocols to restore synchrony.
4. *Temporal profiling of willpower:* Willpower unfolds over time and may falter predictably under prolonged load. Predictive analytics from connectivity data can schedule proactive reframing breaks before performance collapse occurs.
5. *Differentiating acute vs. chronic disruptions:* Acute lapses (e.g., during a long EVA simulation) require immediate corrective drills, while chronic drains (e.g., inflammation, persistent sleep debt) require systemic solutions, such as medical evaluation, nutritional support, and long-term resilience training.

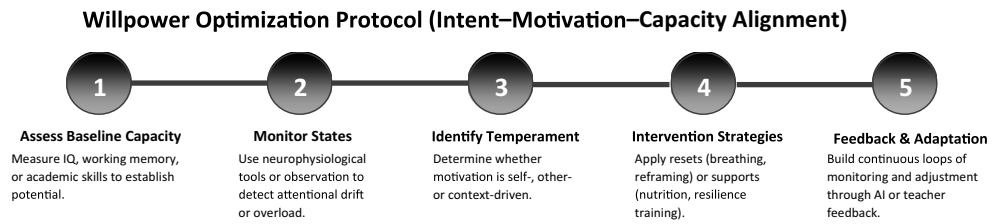


Figure 5.
Willpower optimization protocol – five adaptive steps for aligning intent, motivation, and capacity in both professional and educational contexts.

By embedding these strategies into training and operational protocols, it was found that willpower can be treated as a manageable, measurable, and improvable construct. Rather than being a mysterious inner resource, it becomes a neuroergonomic variable – subject to monitoring, alignment, and optimization in the same way as any other performance-critical factor.

6.8 Applied toolkit: From space missions to schools

Although willpower is often treated as an abstract or internal resource, it can be operationalized as a structured intervention process. **Figure 5** summarizes a five-step Willpower Optimization Protocol that aligns intent, motivation, and capacity across both professional and educational contexts. Although the framework was first tested in high-stakes domains such as aerospace and clinical training, its structure generalizes conceptually to education. The following protocol illustrates how the same logic of intent–motivation–capacity alignment can be adapted – not transplanted – to support persistence and self-regulation in classrooms. This chapter proposes that a structured Willpower Optimization Protocol can guide interventions for both professionals and students:

Step 1. Assess Baseline Capacity (Traits): Measure IQ, working memory, or technical/academic skills to establish potential.

Step 2. Monitor States (Network Dynamics): Use neurophysiological tools or behavioral observation to detect attentional drift or overload.

Step 3. Identify Temperament (Motivational Anchors): Determine whether the individual is self-referential, other-referential, or context-driven in motivation.

Step 4. Intervention Strategies: Apply acute resets (breathing, reframing, breaks) or chronic supports (nutrition, sleep hygiene, resilience training).

Step 5. Feedback & Adaptation: Build continuous loops of monitoring and adjustment, using AI dashboards in missions or teacher observations/self-reports in schools.

Checklist for practitioners:

- Does the task feel self-relevant?

- Is the individual's state stable (not overloaded, fatigued, or distracted)?
- Are motivational anchors engaged?
- Are there acute or chronic drains undermining willpower?

6.8.1 Applied example: Classroom persistence

Consider a high school student working through a multi-step algebra problem set. Standard assessment may flag errors only after performance has already broken down, but monitoring based on the Performance Triad can detect the early onset of cognitive fatigue – for instance, reduced frontoparietal β -coherence coupled with declining DMN stability, signaling waning motivational engagement. Instead of waiting for disengagement, the system could insert a micro-intervention: a brief motivational reframing prompt (e.g., linking the task to the student's personal goals), a paced recovery pause, or a context-shift exercise. Pilot studies and illustrative applications suggest such interventions help students sustain persistence without overtaxing their capacity, showing how the Performance Triad can extend conceptually from mission-critical environments to everyday classrooms. Where EEG tools are not available, teacher observation of attentional drift and behavioral self-reports can serve as practical proxies.

6.8.2 Applied example: STEM inquiry and persistence

In a middle school robotics lab, students work in small teams to troubleshoot a malfunctioning sensor. While cognitive readiness and situational awareness are evident in their problem-solving strategies, motivational monitoring reveals a subtle pattern: one student begins to disengage after repeated failed attempts, with EEG signals (or behavioral proxies such as posture, gaze aversion, or reduced verbal contribution) indicating declining self-relevance and rising fatigue. The adaptive system introduces a short reframing cue, reminding the student of the project's connection to a school-wide robotics competition. This motivational anchor restores persistence, and the team completes the task. Here, the Performance Triad supports not only technical skill and awareness but also the sustained willpower needed for inquiry-driven STEM learning.

6.8.3 Applied example: Writing and extended tasks

In writing-intensive assignments, such as composing a research essay, learners may show intact readiness and awareness but falter in persistence due to fatigue, frustration, or self-doubt. Motivational monitoring – whether via neurophysiological signals or teacher-supported observation – enables timely micro-interventions such as guided mental rehearsal, value-based prompts, or brief recovery breaks. These supports sustain willpower by realigning intent, motivation, and capacity. Across STEM and humanities domains, the Performance Triad ensures not only readiness and awareness but also the motivational scaffolding required for deep, sustained learning.

7. Ethical and implementation considerations

In educational contexts, motivational monitoring must also respect developmental psychology principles. Children and adolescents are particularly sensitive to the balance between intrinsic and extrinsic motivation. While gentle nudges can sustain persistence, excessive reliance on external prompts risks undermining self-determination and fostering dependency on feedback loops. Ethical design must, therefore, prioritize the cultivation of intrinsic motivation – linking tasks to curiosity, identity, and personal goals – rather than defaulting to external reinforcement. Long-term resilience in learners depends not only on supporting persistence in the moment but also on strengthening their internal capacity for self-driven engagement.

Brain-computer-enabled, trait-state adaptive systems sit closer to the mind than traditional training tools. That proximity brings real benefits (earlier help, fewer lapses) and real responsibilities (privacy, consent, fairness, and restraint). The points below summarize what responsible use should address without prescribing a particular operational model.

Key concerns at a glance

- **Informed consent (plain language):** State what is collected (signals and derived features), why it is collected, for how long, and how to opt out or delete the data.
- **Privacy and data minimization.** Prefer feature-level summaries over raw EEG; limit retention; protect access; encrypt in transit and at rest.
- **Transparency.** Users should be able to ask, “Why did I get a cue?” and receive a simple, truthful explanation.
- **Human autonomy and over-monitoring:** Avoid constant nudging; keep people in control, and use restraint to prevent technology dependence.
- **Fairness & bias:** Check that thresholds and benefits are comparable across age/skill groups and do not systematically disadvantage any subgroup.
- **Interpretation without stigma:** describe vulnerabilities as trainable and context-dependent; avoid labels that imply fixed traits.
- **Context and cultural fit.** Match intrusiveness and language to the setting (classroom, cockpit, clinic); respect norms and constraints.
- **Safety boundaries:** Do not present performance tools as medical diagnoses or treatments unless you are operating under clinical governance.
- **IP separation and brand clarity.** Keep trait-training content, state monitoring, and platform/delivery described as distinct components; do not imply shared ownership.

- Evidence and claims discipline. Report what the system prevents (e.g., prevented-lapse rate, lead-time) and avoid making claims beyond the data collected.

This chapter argues for proactive, anticipatory support – but with these safeguards in view, ensuring that measurable gains do not come at the expense of privacy, autonomy, or trust.

Beyond CR and SA, motivational data introduces unique ethical challenges. If BCIs can measure persistence or detect waning willpower, there is a risk of misuse – ranging from manipulative nudges to coercive performance demands. Safeguards must, therefore, explicitly cover the collection, interpretation, and application of motivational indices, ensuring that learners and professionals retain autonomy over how their persistence is supported. Motivation monitoring must be used to empower, not to control.

These risks are especially salient in educational settings, where motivational monitoring intersects with student autonomy and developmental sensitivity. BCIs that detect lapses in persistence must be carefully designed to support – not coerce – learners. For instance, nudging a student to persist in healthy challenges is constructive, but pressuring them to continue beyond safe cognitive or emotional limits risks undermining trust and intrinsic motivation. Ethical deployment, therefore, requires culturally sensitive framing, transparent data policies, and student agency in deciding how motivational feedback is applied.

7.1 Equity and access in education

A further ethical consideration is equity of access. If BCI-enabled adaptive systems that measure motivation are available only to elite institutions or high-resource learners, they risk widening existing educational divides. Students in underserved schools may be left with outdated, reactive assessment methods while their peers benefit from proactive motivational scaffolding. Ensuring broad accessibility and affordable implementation pathways is therefore essential. Equity is not only a matter of fairness but also of research validity: without diverse deployment, findings about motivation and performance risk being biased toward narrow populations.

8. Discussion

This chapter extends existing frameworks – such as CR [90–92], SA [4], the SRK model [5], and classical learning theories like the Ebbinghaus forgetting curve [6] – by operationalizing them inside a real-time, BCI-enabled adaptive loop. Critically, the authors expand these traditions by adding motivation/willpower as a third, measurable leg of the Performance Triad, alongside readiness and awareness. Importantly, motivation/willpower is not an isolated reservoir but an emergent property of the alignment of intent (direction), motivation (drive), and capacity (resources), which together sustain persistence under load. By embedding motivation into the trait–state framework, the authors provide a more complete account of why individuals falter or persist under load. This reframing highlights that resilient performance is not simply a matter of ability and awareness, but

equally of sustaining effort when conditions degrade. Importantly, this reframing is not theoretical alone: it is grounded in years of developing and applying NeuroCoach® and IQity® systems across diverse clinical and non-clinical contexts, including education, neurorehabilitation, aerospace analogs, athletics, and corporate training. These cumulative applications provide the empirical foundation for the operational framework advanced in this chapter.

Operationally, the core contribution is to make CR, SA, and M continuous, measurable, and trainable inside the same loop that drives adaptation: (i) sense EEG/connectivity plus task signals; (ii) predict short-horizon lapse risk; (iii) gate pre-emptive cues (mid-band tonic alertness with two-hit confirmation); (iv) cue once with a short lockout; and (v) evaluate using prevented-lapse rate, lead-time, intervention yield, and false-alarm cost. This ties Section 2's theory to the CR/SA/M indices defined in Section 3 and the anticipatory control in Section 4, and it explains the cross-domain pattern in Section 5 (shared loop, domain-specific tuning). Within this loop, willpower should be understood not as a standalone variable but as the *sustained enactment* that emerges when intent is clearly anchored, motivational energy is available, and cognitive capacity is sufficient to execute. This alignment is what transforms motivation into durable persistence under pressure.

The integration of CR, SA, the SRK model, and the Ebbinghaus Forgetting Curve into a BCI-enabled trait–state–motivation framework represents a significant departure from traditional learner-centered paradigms. Historically, development in education and training has been reactive – identifying lapses after they occur and remediating them through behavioral strategies, self-report reflection, or targeted skills practice [93]. While that model can help, it cannot detect and intervene in real time, allowing cognitive inefficiencies, attentional breakdowns, and motivational lapses to accumulate before they become visible.

The trait–state–motivation distinction, operationalized via a trait-training component and a state-monitoring component [8, 24], addresses this gap directly. Trait measures capture stable capacities – working memory, cognitive flexibility, inhibitory control – that shape learning potential. State measures capture moment-to-moment fluctuations in attention, stress regulation, and motivational salience, which determine whether that potential is realized in a given episode. Unifying these into one adaptive protocol allows dynamic tailoring of demand so the learner is neither under- nor over-challenged relative to current readiness. In classrooms, this same loop can anticipate motivational lapses during problem-solving or writing tasks, sustaining persistence before disengagement sets in.

Viewed through the lens of network neuroscience, the relevance of this framework becomes sharper. High IQ or strong baseline performance does not immunize a learner from network vulnerabilities. Disruptions within executive, salience, or default-mode networks can reduce resilience under load, slow task switching, or impair sustained focus [94]. Health factors – e.g., low-grade systemic inflammation [95], sleep deficits, or endocrine dysregulation – can transiently weaken coherence, producing unpredictable variability even in otherwise high-functioning individuals. By incorporating EEG-based connectivity into ongoing training, the program can detect and flag these transient disruptions and temporarily shift to recovery-focused tasks until stability returns.

Coupling the loop with the SRK model adds precision regarding how performance fails and recovers. Under increasing complexity and time pressure, people often regress from knowledge-based reasoning to rule-based or even skill-based modes [5].

NASA-aligned work has shown that such regressions can be anticipated by EEG correlates (e.g., narrowed attentional focus, increased motor preparation, frontal-theta shifts) and stabilized before critical errors [8].

Operationalizing the Ebbinghaus curve further strengthens the proactive stance: spacing and retrieval become state-gated rather than clocked. By tracking not only task accuracy but also neurophysiological indicators of consolidation, the system can time reinforcement before decay crosses a threshold [6, 64]. In practice, this means scheduling brief retrieval checks immediately after recovery to cement gains and deferring difficult upshifts until CR is stable.

Limitations remain. Ethically, privacy, consent, and potential misuse of neurocognitive data require explicit safeguards [96]. Technically, robust signal acquisition and artifact handling outside laboratories are non-trivial; portability and usability must not compromise interpretive accuracy. Empirically, while early implementations report promising gains across clinical and high-performance contexts [8, 24], larger comparative studies are needed to quantify effects by domain, learner profile, and task type.

Adoption will also demand cultural shifts. Moving from retrospective assessment to continuous monitoring and adaptation asks instructors, trainers, and learners to become comfortable with neurofeedback, to trust transparent algorithmic decisions, and to appreciate the nuanced interplay between traits, states, and motivational dynamics.

In sum, BCI-enabled adaptive learning is not merely a technological add-on. By making long-standing constructs measurable and actionable in real time, it reframes support from reactive remediation to anticipatory stabilization – bridging theory and practice and enabling consistent, auditable gains across domains. In doing so, it exemplifies how BCI can responsibly bridge technology, education, and ethics to support resilient performance.

9. Conclusion

This chapter reframes BCI-enabled learning as a proactive, anticipatory control problem: detecting and stabilizing the cognitive system before performance breaks. By defining CR and SA as continuous indices, adding a short-horizon early-warning layer with anticipatory cueing and lockouts, and reporting proactive outcomes (Prevented-Lapse Rate, lead-time, intervention yield, false-alarm cost), the authors move long-standing theories (CR, SA, SRK, Ebbinghaus) from abstraction to auditable practice. The same loop applies across domains; what changes are features, thresholds, interventions, and success criteria – making the approach portable without over-generalizing.

Two commitments follow: ethically, the loop must preserve privacy, autonomy, fairness, and clear boundaries between performance support and healthcare. Operationally, claims should be matched to evidence using the evaluation summary provided (AB/ABA and crossover).

In summary, the integration of BCI-enabled monitoring with trait-state-motivation modeling marks a transition from reactive to proactive education and training. By extending the framework to include motivation/willpower alongside readiness and awareness, the authors establish the Performance Triad as the foundation of resilient performance. This triadic model ensures that learners and

professionals are not only prepared and perceptive but also persistently engaged – transforming education and high-stakes operations alike. In doing so, it embodies the promise of this volume: using BCIs to bridge technology, education, and ethics in ways that are both scientifically grounded and human-centered.

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Effects of Brain–Computer Interfaces on Upper and Lower Limb Function Rehabilitation After Stroke

Feilong Zhu, Yu Wu and Ming Zhang

Abstract

Brain–computer interfaces (BCIs) represent a form of neurotechnology that enables direct interaction with the environment by interpreting brain signals, without relying on conventional neuromuscular pathways. These systems utilize physiological signals such as electroencephalography (EEG) to allow users to control external equipment directly, thereby offering rehabilitation support and daily life assistance for individuals with motor function impairments. BCI is recognized for its high safety profile, ease of use, and demonstrated efficacy in functional recovery, making it increasingly relevant in clinical settings. Based on the method of signal acquisition, BCI is classified into invasive and non-invasive types, with non-invasive BCI being more commonly used in clinical practice due to lower procedural risks and greater usability. A typical BCI system operates through five core stages: signal acquisition, preprocessing, feature extraction, pattern classification, and control output. Currently, this technology has been effectively applied in the rehabilitation of motor functions in stroke patients, showing particularly promising results in the recovery of upper limb and walking functions. By promoting neuroplasticity in the brain, BCI can help stroke patients regain motor function. However, BCI still faces challenges such as signal quality issues, standardized treatment protocols, and treatment selection difficulties. Despite these limitations, BCI offers a promising approach for motor rehabilitation after stroke. Further research is needed to address existing challenges and improve clinical outcomes.

Keywords: brain–computer interfaces, stroke, upper limbs, lower limbs, motor function, rehabilitation

1. Introduction

Stroke, clinically referred to as cerebrovascular accident, is an acute neurological condition caused by the sudden blockage or rupture of cerebral blood vessels. This disruption leads to impaired blood flow to brain regions, resulting in insufficient cerebral perfusion and consequent neural tissue damage. It is broadly classified into

two main types: ischemic stroke, caused by cerebral artery stenosis or thrombosis (e.g., cerebral infarction), and hemorrhagic stroke, resulting from vessel rupture (e.g., intracerebral or subarachnoid hemorrhage). Ischemic stroke constitutes 60–80% of cases, while hemorrhagic stroke accounts for 10–30%. Globally, stroke is a leading cause of morbidity and mortality, with approximately 12.2 million new cases annually and over 100 million people living with its long-term effects [1]. China bears the highest lifetime stroke risk globally, with an estimated 17 million survivors in 2024; this number is projected to increase to 20 million by 2030 [2]. The economic burden is substantial, with global costs estimated at USD 460 billion in 2019, primarily attributed to direct medical expenses and long-term care [3]. Stroke consequences are profound, including high mortality, disability, and recurrence rates. It is the leading cause of adult death and disability in China, with an 80% disability rate among survivors. Motor dysfunction, particularly in the upper and lower limbs, is one of the most debilitating consequences of stroke, affecting approximately 80% of survivors in the upper limbs and 60–70% in the lower limbs [4, 5]. These impairments severely restrict activities of daily living (ADLs) and functional independence, while also imposing a significant emotional and psychological burden on both patients and their caregivers. Addressing upper and lower limb motor dysfunction is critical for enhancing patients' quality of life, improving functional independence, and reducing the long-term economic burden on healthcare systems and families.

Conventional rehabilitation strategies for stroke patients often involve peripheral training techniques. These may include muscle and joint exercises, functional electrical stimulation (FES), and other techniques aimed at enhancing neuromuscular function. However, this type of treatment does not directly target the damaged brain and does not optimize its therapeutic impact [6, 7]. Neurofeedback is a form of biofeedback that provides stroke patients with new opportunities by instructing them to independently modify their specific brain activity, thereby causing behavioral changes. The patient can receive information on measured brain activity visually, audibly, or through other means [8]. Fundamentally, neurofeedback operates by engaging the brain's plasticity – the ability of neural tissue to reorganize after injury. This process encourages remaining neurons near the damaged area to form new connections, restore communication with the affected limbs, and ultimately lead to functional recovery.

Brain–computer interfaces (BCIs) are systems designed to decode and convert neural activity into executable commands, thereby facilitating direct interaction between the human brain and computers or machines. They involve the acquisition of brain signals (e.g., electroencephalography [EEG]), processing of these signals, and the generation of control commands to interact with the environment. BCI has shown significant potential in rehabilitation, particularly for stroke patients. In stroke rehabilitation, BCI is used to assist in the recovery of motor functions, especially in the upper limbs. Studies have demonstrated that BCI can improve upper limb function, enhance motor imagery, and promote neuroplasticity in stroke patients [9]. The first case study describing the use of BCI in stroke rehabilitation was published in 2009 [10]. Subsequently, various studies have confirmed the clinical efficacy of BCI technology in upper limb motor rehabilitation and supported its application in the limb motor rehabilitation of stroke patients, which can significantly increase the scores of Fugl–Meyer Assessments (FMA) [11–13]. While BCI has also been investigated for lower limb rehabilitation, the evidence base is

currently more limited, with some studies suggesting potential benefits. However, the application of BCI in lower limb rehabilitation is still in the early stages of development and requires further research to establish its efficacy and clinical utility.

BCI, as a cutting-edge multidisciplinary technology, is increasingly gaining attention and application. BCI translates recorded brain signals into control commands, enabling individuals to interact directly with external devices without relying on speech or physical movement. This personalized and interactive approach to rehabilitation training not only enhances patient engagement but also improves therapeutic outcomes. This chapter elaborates on the clinical efficacy of BCI technology in improving rehabilitation outcomes for stroke patients with upper and lower limb dysfunction. Additionally, it addresses the current challenges facing BCI's clinical implementation and explores future research directions.

2. Concept and classification of BCI

What is the BCI? Imagine the brain as an orchestra and each neuron as a musician. After a stroke, some musicians (motor cortex neurons) can still play, but their instruments (muscles) are out of tune or disconnected. A BCI acts like a conductor who “listens” to the surviving musicians and instantly translates their rhythm into new sheet music for robotic arms, functional electrical stimulators, or virtual avatars – bypassing the damaged pathways.

BCI, also referred to as a brain–machine interface (BMI), forms a direct communication link between neural activity and external hardware. This technology bypasses the body's conventional neuromuscular output channels, enabling users to interact with and control their environment through the direct translation of brain signals (e.g., recorded via EEG) into commands [14]. A critical pedagogical point is that a system which only records and analyzes brain signals is not a BCI; the defining feature is the closed-loop operation, where brain activity is processed in real-time to provide immediate feedback to the user or to control a device. This feedback is essential for learning and neuroplasticity, which is the fundamental mechanism behind its application in stroke rehabilitation. Through this loop, BCI technology allows users to operate a wide range of external equipment, including computers, communication aids, assistive devices, and neural prosthetics, and offers considerable promise for improving daily living independence and functional recovery among individuals with neurological impairments. In the long term, these advancements may also contribute to a reduction in dependency on continuous care and lower overall healthcare expenditures.

Generally, the operation of a BCI system involves three key stages [1]: signal acquisition [2], signal processing, and [3] device control. To make these abstract stages concrete, consider “Mr. Tanaka,” a 62-year-old ischemic–stroke survivor with severe left hemiparesis.

- Stage 1 – Signal acquisition: While Mr. Tanaka attempts to open his paretic hand, a 32-channel EEG over the right motor cortex captures μ -rhythm desynchronization.

- Stage 2 – Signal processing: A machine-learning classifier trained on its own data translates the desynchronization pattern into a “hand-open” probability score, updated every 100 ms.
- Stage 3 – Device control: When the probability exceeds 70%, a soft robotic glove inflates, physically opening his hand. Seeing the movement provides immediate visual and proprioceptive feedback, closing the sensorimotor learning loop.

BCI is primarily classified, based on the location of signal acquisition, into two categories: invasive brain–computer interface (IBCI) and non-invasive brain–computer interface (NBCI) [14]. This fundamental distinction directly dictates the types of neural signals that can be recorded, each with its own set of capabilities and limitations. Non-invasive BCI, typified by electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI), offers a safe and accessible means of recording brain activity from the scalp. However, these signals often face challenges such as low spatial resolution or poor temporal fidelity. In contrast, invasive BCI, such as electrocorticography (ECoG) and intracortical neuron recording (INR), are surgically implanted to capture high-fidelity signals directly from the cortical surface or within the brain tissue, providing superior spatial and temporal resolution at the cost of requiring a surgical procedure. The choice of modality is, therefore, a critical decision, balancing trade-offs between signal quality, practicality, and patient risk.

3. Working principles and theoretical basis of BCI in clinical treatment

3.1 Working principles

The workflow of BCI systems for stroke rehabilitation typically comprises five sequential stages [1]: signal acquisition [2], preprocessing/signal enhancement [3], feature extraction [4], classification, and [5] control interface. Specialized devices first acquire brain signals from the stroke patient. These raw signals are then amplified and filtered to improve quality. Subsequently, discriminative features are extracted from this preprocessed input. A classification algorithm translates these features into output commands. Finally, these commands are conveyed to external assistive devices, enabling the patient to perform specific actions and complete the feedback loop (see **Figure 1**) [15].

3.2 Theoretical basis: Neuroplasticity and its role in BCI

BCI establishes a novel non-muscular communication channel. By training stroke patients to modulate their brain signals, individuals with motor dysfunction can utilize these signals for communication and movement control, effectively bypassing damaged neuromuscular pathways. This process translates the brain’s neural activity into artificial output commands. These commands serve to restore, replace, or compensate for lost neural outputs, thereby facilitating interaction between the brain and the external environment. This approach offers a promising new paradigm for rehabilitating patients with severe motor impairments. When conventional motor pathways are compromised, BCI systems can employ brain signals as an

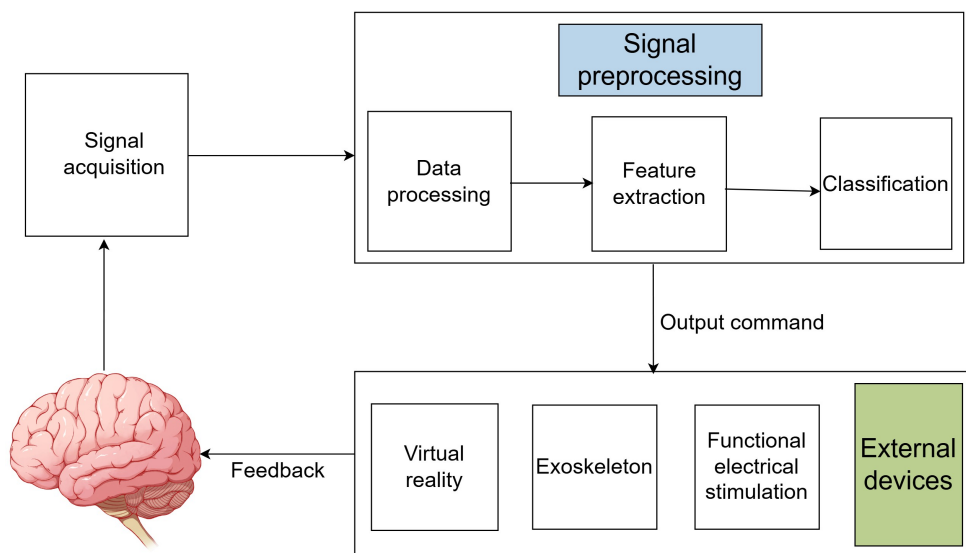


Figure 1.
 The working principles of BCI.

alternative channel for communication or device control. Furthermore, they may potentially modulate neuroplastic processes within the brain, promoting recovery of normal motor function [14].

The fundamental theoretical premise supporting BCI-mediated rehabilitation is neuroplasticity – the nervous system’s remarkable, lifelong capacity to reorganize its structure, function, and connections in response to experience, learning, and injury [16]. This inherent adaptability is the very foundation for functional recovery after stroke. It is not a passive process; the type and extent of plastic changes are highly task-specific, experience-dependent, and influenced by the motivation of the individual. Consequently, leveraging neuroplasticity – specifically, the functional reorganization of brain structure and its inherent adaptability to enhance post-stroke functional recovery – is a central focus and ongoing challenge in rehabilitation research.

Key mechanisms underpinning neuroplasticity include:

- **Functional reorganization:** Adjacent brain areas can take over functions lost due to lesions.
- **Synaptic plasticity:** Strengthening (long-term potentiation, LTP) or weakening (long-term depression, LTD) of synaptic connections based on activity.
- **Structural changes:** Dendritic sprouting, axonal regeneration, and the formation of new synapses (synaptogenesis).

BCI systems directly harness these principles by providing a closed-loop where brain activity drives peripheral feedback. When a patient imagines moving their paralyzed limb, the BCI detects the associated sensorimotor rhythm (e.g., μ -rhythm) desynchronization, decodes this intention, and triggers an external device like an

FES or robotic orthosis to execute the movement. This process creates a tight perceptual coupling between intention and action, providing the brain with the intense, repetitive, and reward-based (contingent) experience necessary to drive plastic changes. Evidence shows that even a single hour of BCI training can induce measurable changes in neuronal structure and function, highlighting its potent role in modulating brain plasticity.

Supporting this, neuroimaging studies (e.g., fMRI) demonstrate that BCI-based interventions can lead to more normalized cortical activation patterns in stroke-affected hemispheres. Furthermore, research indicates that the brain's intrinsic "body map" remains stable even after limb loss or stroke, suggesting that BCI is not creating new functional areas but rather reactivating and strengthening latent pathways that the brain has been "waiting to reconnect" [17]. By promoting targeted neural activity and combining it with peripheral stimulation, BCI leverages characteristic brain signals to integrate sensory input and central activation, forming a normalized motor pattern. This synergistic approach enhances muscle activity and promotes the restoration of motor function by guiding and accelerating the brain's innate plastic potential.

4. Application of BCI in upper limb rehabilitation after stroke

BCI systems frequently incorporate training protocols integrated with external assistive devices. By acquiring EEG signals and decoding the patient's movement intentions, these systems translate neural information into executable commands transmitted to external hardware. The connected device then implements these instructions while delivering somatosensory or visual feedback, establishing an active closed-loop system. This integrated process enables patients to modulate neural activity, thereby accelerating neuroplasticity and facilitating motor function recovery. Commonly utilized external devices include FES, upper-limb rehabilitation robots, and visual feedback interfaces.

4.1 FES training based on BCI

FES delivers programmed, low-frequency pulsed currents to the neuromuscular system, eliciting functional movements that mimic voluntary motion. This mechanism compensates for or replaces lost neurological function. In a study addressing post-stroke shoulder subluxation, Jang et al. administered either BCI-FES or standalone FES (20 minutes per session, totaling 30 sessions over 6 weeks; stimulation: 15-second duration, 35 Hz, 1–50 mA). Results demonstrated BCI-FES's superior efficacy in reducing subluxation and improving shoulder flexion/abduction compared to FES alone [18]. Biasiucci et al. conducted BCI-FES training for 27 stroke patients with severe hand paralysis (60 minutes per session, 2 times per week for 5 weeks); the FES current intensity was 10–25 mA, and the frequency was 16–30 Hz [19]. After training, the FMA score in the upper limbs of the experimental group was significantly higher than that in the control group, and the effect could be maintained for 6 to 12 months after the end of the training, which shows that the combined training of BCI and FES can more effectively improve the upper limb motor function of patients with chronic stroke. Tabernig et al. conducted BCI-FES training on 8 stroke patients (60 minutes per session, 4 times

per week); FES produced a bidirectional rectangular pulse current with a maximum intensity of 40 mA, a frequency of 2.5pps, and a duration of 0.2 ms [20]. After training, the patient's upper limb FMA scores were significantly improved, and the spasticity, active flexion, and quality of life of the elbow and wrist joints were enhanced.

4.2 Upper limb rehabilitation robot training based on BCI

Upper limb rehabilitation robots are interactive electromechanical systems categorized into two primary configurations: exoskeleton and end-effector types. Exoskeleton designs assist limb movement by precisely controlling displacement across articulated segments, while end-effector configurations mobilize limbs through distal application points. These robotic systems enable repetitive, high-intensity, task-specific training that stimulates, reactivates, and integrates somatosensory inputs within motor circuits. By promoting sensorimotor reorganization, they demonstrate particular efficacy in fine motor rehabilitation [21]. BCI systems translate patients' neural activity into control signals for upper-limb rehabilitation robots, enabling these devices to drive or assist standardized limb movements. Crucially, this process maintains the patient's direct control over the robotic system. Ang et al. (2014) demonstrated the therapeutic value of this integration, reporting that 136 sessions of BCI-controlled exoskeleton training achieved comparable functional recovery to 1,040 sessions of conventional robotic therapy [22]. In a multicenter randomized controlled trial, Frolov et al. assigned 55 stroke patients to active BCI-controlled hand exoskeleton training, while 19 controls received passive exoskeleton training. Both groups underwent concurrent physical therapy (30 minutes each session, total 10 sessions) [13]. While both demonstrated improved FMA and Action Research Arm Test (ARAT) scores, the control group showed no significant gains in grasp, pinch, or gross movement subdomains. Crucially, the BCI group exhibited clinically meaningful improvement (minimum clinically important difference) in FMA and ARAT outcomes at rates 4.3-fold and 2.3-fold higher than controls, respectively. Complementing these findings, Bhagat et al. implemented BCI-driven dynamic elbow exoskeleton training in 10 stroke patients (3 times/week $\times$ 4 weeks), observing significantly enhanced FMA/ARAT scores with improved movement speed and fluency post-intervention [23]. Similarly, Chen et al. randomized 14 patients to BCI or control therapy, reporting higher relative functional improvement (12.77% vs. 7.14%) and a greater proportion of patients achieving good motor recovery in the BCI group (57.1% vs. 28.6%) [24].

4.3 Multimodal feedback training based on BCI

As established, BCI-driven FES and upper-limb rehabilitation robots provide proprioceptive and visual feedback, effectively enhancing post-stroke motor recovery. Crucially, different feedback modalities elicit distinct therapeutic effects, suggesting that multimodal BCI-integrated feedback may amplify clinical outcomes [25]. Supporting this, Miao et al. implemented BCI-FES training with concurrent virtual limb visualization and FES-induced somatosensory feedback, leveraging dual visual-sensory pathways to improve upper-limb function in chronic stroke patients [26]. Similarly, Hu et al. demonstrated that BCI training integrating both sensory

and visual feedback significantly enhances motor recovery in the upper extremities and hands of chronic stroke survivors [27].

5. Application of BCI in lower limb rehabilitation after stroke

5.1 FES training based on BCI

FES delivers targeted electrical pulses to directly activate muscles, enhancing strength, reducing spasticity, and supporting neural recovery. It combines FES with a BCI system to activate muscles by decoding brain signals and converting them into electrical stimulation signals, thereby restoring or improving the motor execution ability of patients with motor dysfunction caused by nerve injury. McCrimmon et al. explored the safety and feasibility of FES systems controlled by BCI in post-stroke gait rehabilitation treatment [28]. They recruited nine patients with post-stroke gait dysfunction who received 12 hours of BCI-FES training. The study showed that FES treatment controlled by BCI is safe for stroke patients and demonstrated potential effects on some participants in improving gait speed and motor function. However, this study focused on the verification of safety. The feasibility of motor function recovery in the lower limbs still requires further clinical trials to verify its efficacy. Chung et al. explored the therapeutic effect of the BCI-FES system on the balance and gait function of patients with chronic stroke [29]. Twenty-six stroke patients were randomly assigned to two groups. The experimental group adopted the BCI-FES intervention method, while the control group used the FES intervention (three times per week for five weeks). In the BCI-FES training, the patients focused on the ankle dorsiflexion movement displayed on the monitor screen, where EEG signals were recorded and processed in real time to generate specific brain wave patterns. After reaching the preset concentration threshold, the BCI system activated the FES device and sent electrical stimulation to the target muscles, forming a closed-loop feedback system. The experimental results showed that FES training with BCI led to greater improvements in gait speed and stride frequency compared to FES training alone, proving the potential effectiveness of the BCI-FES system in gait functional recovery. However, it also highlighted the need for further research to verify its long-term effects on balance and other aspects, as well as to explore how to optimize the training scheme to improve overall rehabilitation outcomes.

The BCI-FES integration promotes effective neuromuscular unit recruitment while augmenting patient engagement through real-time feedback. This dual mechanism stimulates central nervous system plasticity, providing an advanced therapeutic approach for post-stroke motor dysfunction that circumvents impaired neural pathways, thereby accelerating functional recovery and improving quality of life. Notably, emerging evidence indicates FES-induced analgesic effects can be leveraged within BCI systems as a novel feedback modality to enhance motor recovery – establishing an empirical foundation for clinical implementation of this integrated neurorehabilitation technology.

5.2 Exoskeleton robot training based on BCI

The BCI-exoskeleton system represents an emerging neurorehabilitation strategy that synthesizes the capabilities of both technologies. For stroke patients with

lower-limb motor and gait impairments, this integrated system decodes movement intention into exoskeleton control signals, enabling volitional gait execution through robotic actuation. By delivering multimodal proprioceptive and kinesthetic feedback during movement, it enhances sensorimotor integration while promoting structural and functional neural reorganization. This intention-driven closed-loop neuromodulation establishes a novel therapeutic paradigm for lower-limb functional recovery.

Barria et al. found that using a BCI system with visual and tactile stimulation can more accurately decode the user's motion intentions [30]. Through this multimodal stimulation method, the system's capture and analysis of the user's neural activity patterns are optimized, providing strong support for the reliability and efficiency of human-computer interaction. In a study of the lower limb function of 28 stroke patients, the experimental group received BCI-controlled robot therapy combined with physical therapy, while the control group received only physical therapy (6 times/week $\times$ 4 weeks) [31]. In BCI training, visual stimulation was used to trigger steady-state visual evoked potential. The system decoded the generated steady-state visual evoked potential and identified the user's motor intention to control the lower limb rehabilitation robot, helping patients complete various motor tasks, such as starting walking, accelerating walking, stopping, etc. Patients could understand their control effects through the virtual character movement on the screen, and the results show that exoskeleton robots controlled by BCI combined with physical therapy are effective strategies to improve lower limb motor functions in stroke patients. In this study, the BCI system adopts an active and passive collaborative stimulation method. Visual stimulation provides active stimulation for motor control neural pathways by activating the mirror neuron system, while robotic assistive devices provide passive stimulation for motor perception neural pathways, thereby enhancing the sensory feedback mechanism during motor learning. However, in this study, there was no statistically significant difference in the recovery of lower limb motor function between the experimental group and the control group, and it only showed enhancement of motor function. More studies are needed in the future to verify its therapeutic effect. Yuan et al. randomly assigned 30 patients with early subacute ischemic stroke to study the lower limb motor function with BCI-controlled stamping training and traditional stamping training (6 times/week $\times$ 2 weeks) [32]. During the training process, the patient was asked to focus on the virtual characters on the screen and try to imagine completing the treadmill task through the lower limbs. During the training, the patient's brain signal was continuously recorded, and the attention index was calculated through the signal processing algorithm. The lower limb rotation speed of the treadmill training robot was controlled according to the patient's attention index. The system, based on the real-time attention index, provides visual, auditory, and somatosensory feedback, encouraging patients to actively participate. The research results show that the lower limb parts of the Fugl-Meyer rating scale of the two groups of patients have improved. Compared with traditional treadmill training, the treadmill training system controlled by the BCI interface can more effectively improve the lower limb motor function of patients with early subacute stroke. The treatment mechanism may be that the system combines neurofeedback and multimodal feedback to simultaneously train the dual tasks of motor and cognition, thereby activating the plasticity of the brain and effectively promoting the recovery of lower limb motor function in stroke patients.

Clinical evidence confirms the therapeutic value of BCI–exoskeleton systems in neurorehabilitation. By integrating multisensory feedback (visual, auditory, tactile),

these systems significantly enhance patient engagement and accelerate functional recovery. However, a critical research frontier remains: optimizing personalized multimodal feedback schemes that accommodate individual patient differences while addressing complex human-computer interaction demands in stroke rehabilitation. Resolving this challenge is essential for maximizing therapeutic outcomes.

5.3 Virtual reality (VR) training based on BCI

Virtual reality technology provides users with an immersive three-dimensional environment. This high degree of immersion and interaction can improve the initiative and enthusiasm of patients' rehabilitation training, better control the BCI system, and provide strong technical support for the recovery of motor function in stroke patients.

In the study of the BCI-VR system for post-stroke gait rehabilitation, Luu et al. proposed recording EEG signals during walking on a treadmill to predict the angles of the hip, knee, and ankle joints of the lower limbs, and to control the walking of roles in the virtual environment to complete closed-loop BCI training [33]. The treatment mechanism may promote central nervous system remodeling in stroke patients, thereby improving gait patterns. The emergence of this system is of great significance to the development of a real-time closed-loop BCI-VR system based on EEG for post-stroke gait rehabilitation and to understanding the cortical plasticity induced by this closed-loop system. Lima et al. proposed an innovative neurorehabilitation platform that integrates transcranial direct current stimulation and a BCI-VR system based on motor imagination [34]. They recruited a patient with a subacute stroke for training five times a week for three weeks to explore its application potential for lower limb rehabilitation. During the training process, the patient was first subjected to 20 minutes of transcranial direct current stimulation to regulate the excitability of the cerebral cortex. Signals related to the patient's movement were collected, processed, and classified to identify brain signals related to pedal movement, which were then converted into the patient's intention to control the movement of the electric pedal. This allowed the patient to directly control external devices through brain signals and connect with the virtual reality ring. The virtual scene synchronization in the environment provided immersive visual feedback. The results show that the integrated system can improve the patient's motor function and sensory ability. Through EEG analysis, significant event-related desynchronization patterns of brain activity were observed in the μ , low β , and high β bands. This indicates that transcranial DC stimulation may enhance the desynchronization of EEG signals related to motor imagination by regulating cortical excitability, while the BCI system captures these signals to achieve control of external devices. Furthermore, this effect is enhanced by providing immersive feedback to promote motor imagination. These interventions may improve the recovery of motor function in patients after stroke by promoting neuroplasticity.

The BCI-VR system leverages immersive environments enriched with multisensory feedback (visual, tactile, auditory) to optimize training engagement and efficacy. This integrated approach reactivates and reorganizes sensorimotor neural networks, facilitating motor dysfunction recovery. Current challenges include limited command diversity and decoding accuracy. Evidence suggests that

innovative BCI paradigms – particularly multimodal systems integrating diverse control/feedback mechanisms – can enhance user experience through improved intention decoding. Such systems enable more naturalistic control schemes, increasing precision in virtual environment navigation while adapting to individual user needs. This personalized approach ultimately delivers more targeted therapeutic outcomes in neurorehabilitation.

6. Application case

Our research team is dedicated to promoting the improvement of upper limb motor function in stroke patients through BCI technology and has accumulated a large number of cases. Below, we present the research results of our team as application cases to enable readers to further understand the application of BCI technology in the recovery of limb motor function in stroke patients.

Between July 2020 and December 2023, a randomized controlled trial was carried out at the Affiliated Xuzhou Rehabilitation Hospital of Xuzhou Medical University [35]. The study was designed to evaluate whether combining kinesthetic motor imagery-based BCI (KI–BCI) training with transcranial direct current stimulation (tDCS) would lead to greater improvement in upper limb motor function in subacute stroke patients compared to applying either KI–BCI or tDCS alone. The inclusion criteria for participants were as follows [1]: A history of stroke diagnosed by computed tomography or magnetic resonance imaging (≥ 14 days and < 180 days) [2]; a score of the Mini-Mental State Examination (MMSE) ≥ 20 [3]; aged between 40 and 80 years old. The exclusion criteria were [1]: History of epileptic seizures [2]; other neurological, neuromuscular, and orthopedic diseases [3]; scalp deformities caused by surgery [4]; having medical instability, such as heart/respiratory failure, deep vein thrombosis, or acute myocardial infarction. If the following conditions occurred during the treatment process, the experimental process of the participant would be terminated [1]: Progressive aggravation of the disease [2]; poor compliance [3]; epilepsy, manic episodes, or other conditions occurring after treatment.

A total of forty-three patients in the sub-acute phase of stroke were enrolled and randomly assigned to one of three intervention groups: a KI–BCI group ($n = 15$), a tDCS group ($n = 14$), and a combined BCI–tDCS group ($n = 14$). **Table 1** shows the interventions of the three groups.

Table 1, cited from our study: Ming Z, Yu W, Fan J, et al. “Efficacy of kinesthetic motor imagery-based brain–computer interface combined with tDCS on upper limb function in subacute stroke.” *Sci Rep.* 2025;15(1):11,829 [35].

7. KI–BCI interventions

To minimize interference with EEG signal quality, all training sessions were conducted in a controlled environment with low lighting and reduced auditory noise. Under the guidance of experienced therapists, participants were instructed to achieve full bodily relaxation and concentrate on performing kinesthetic motor imagery (KMI) tasks (see **Figure 2**). Visual and auditory cues were delivered using the L-B300 EEG Acquisition and Rehabilitation Training System (Zhejiang Mailian Medical Technology Co., Ltd.) to facilitate engagement with the motor imagery task.

Group	Interventions	Dose
KI-BCI	Conventional interventions (30 minutes per session) + KI-BCI (30 minutes per session) treatment	Once a day, five times a week, over a period of four weeks.
tDCS	Conventional intervention (30 minutes per session) + tDCS therapy (30 minutes per session)	
BCI-tDCS	Conventional intervention (30 minutes per session) + tDCS therapy (15 minutes per session) + KI-BCI (15 minutes per session)	

Note: All participants received conventional interventions, including mobilization, neural facilitation techniques, sit-to-stand training, balance training, and functional electrical stimulation.

Table 1.
Interventions of different groups.



Figure 2.
Photograph of the KI-BCI training system. The system comprises an EEG acquisition module for real-time signal recording, a computing unit that analyzes neural data and delivers real-time visual and auditory cues, and an integrated feedback mechanism that provides triggered tactile and motor assistance during task performance.

Participants were specifically asked to imagine themselves performing freestyle swimming in a virtual environment, mentally simulating the motion of their upper limbs alternately pushing against the water to propel forward. Of course, this also included various other task scenarios. Each session did not enforce a fixed number of repetitions but adhered to a strict total duration. The number of effectively completed actions depended on the participant’s real-time motor imagery performance. The system advanced the virtual scenario and activated an attached robotic arm only when the participant’s motor imagery (MI) score exceeded a predetermined threshold.

EEG signals were acquired from prefrontal and motor cortical regions (electrode sites: FP1, FP2, F3, F4, C3, C4, Fz, Cz). The MI score was computed based on a composite similarity metric combining the Pearson correlation coefficient and dynamic time warping (DTW), which aligns two time series

nonlinearly and serves as a widely adopted similarity measure for time-series classification. This approach captured both linear and nonlinear similarities between the participant's real-time EEG and their individualized motion-related cortical potential (MRCP) model.

When the MI score met or exceeded the threshold, the system initiated active-assisted movement mode, wherein a robotic arm (an integrated upper limb measurement and assistance device) guided the participant's affected limb to complete the intended task. This process established a closed-loop interaction between the central nervous system and peripheral limbs – distinguishing it from conventional open-loop robotic training. If the threshold was not met, no assistance was provided, ensuring feedback occurred only during accurate motor imagery.

The intervention was administered once per day, five days per week, over a continuous four-week period.

8. tDCS interventions

The ActivaDose®II portable transcranial direct current stimulator (Wogao Medical Equipment Co., Ltd., Nanjing, China) was employed to deliver non-invasive neuromodulation to participants with subacute stroke. The M1 region of the primary motor cortex was localized using the motor-evoked potential (MEP) module of the Magstim Rapid repetitive transcranial magnetic stimulator (Magstim, UK). The optimal stimulation site within M1 was identified by systematically adjusting the intensity and orientation of the magnetic coil.

A unilateral tDCS montage was adopted for this study, with the anode positioned over the M1 area in the lesioned hemisphere and the cathode placed supraorbitally on the contralateral side. Both electrodes consisted of 5 cm × 5 cm saline-soaked sponge pads. A constant current of 2 mA was applied during each session. Stimulation was administered once daily, five days per week, for a total of four weeks.

To evaluate the recovery of upper limb motor function in stroke patients before and after the intervention, the following clinical assessment scales were employed: the Fugl-Meyer Assessment for the Upper Extremity (FMA-UE), the Motor Status Scale (MSS), the Modified Barthel Index (MBI), and the ARAT.

No significant group differences were observed regarding age, gender, stroke type, or time since stroke onset (**Table 2**). Additionally, baseline scores on clinical outcome measures were comparable across all groups.

Table 2, cited from our study: Ming Z, Yu W, Fan J, et al. “Efficacy of kinesthetic motor imagery-based brain–computer interface combined with tDCS on upper limb function in subacute stroke.” *Sci Rep.* 2025;15(1):11,829 [35].

Following the four-week intervention period, significant differences in motor recovery were observed among the groups. The KI-BCI group demonstrated statistically significant improvements in FMA-UE scores compared to the tDCS group ($P = 0.003$). Similarly, both the KI-BCI group ($P = 0.003$) and the combined BCI-tDCS group ($P = 0.011$) yielded superior MSS results relative to the tDCS-only group. However, no statistically significant intergroup differences were found in the ARAT. Additionally, the MBI score

Variable	KI-BCI (N = 15)	tDCS (N = 14)	BCI-tDCS (N = 14)
Age, years	56.13 ± 8.63	60.79 ± 11.48	54.93 ± 8.73
Gender, n (%)			
Male	8 (57.1)	9 (64.3)	10 (71.4)
Female	7 (42.9)	5 (35.7)	4 (28.6)
Stroke type, n (%)			
Ischemic	10 (66.7)	10 (71.4)	12 (85.7)
Hemorrhagic	5 (33.3)	4 (28.6)	2 (14.3)
Time from the onset, days	44.07 ± 22.63	39.36 ± 12.67	38.00 ± 26.76

Table 2.
Clinical characteristics of the patients.

of the KI-BCI group was significantly higher than that of the tDCS group ($P = 0.005$). A comprehensive summary of these outcomes is provided in

Table 3.

Table 3 cited from our study: Ming Z, Yu W, Fan J, et al. “Efficacy of kinesthetic motor imagery-based brain-computer interface combined with tDCS on upper limb function in subacute stroke.” *Sci Rep.* 2025;15(1):11,829 [35].

Based on the results obtained, KI-BCI training produced marked improvements in both motor function and daily living activities among patients with subacute stroke when compared to tDCS applied alone. Although the combined BCI-tDCS

Variable/group	Pre-intervention	Post-intervention
FMA-UE		
KI-BCI	22.00 ± 0.49	40.50 ± 0.86
tDCS	22.29 ± 1.75	33.93 ± 1.64
BCI-tDCS	22.57 ± 3.26	36.50 ± 4.07
MSS		
KI-BCI	37.14 ± 0.65	58.57 ± 0.98
tDCS	36.71 ± 0.79	51.86 ± 1.36
BCI-tDCS	38.21 ± 1.04	57.93 ± 1.23
ARAT		
KI-BCI	15.93 ± 2.33	26.50 ± 2.94
tDCS	15.07 ± 2.22	19.71 ± 2.09
BCI-tDCS	12.93 ± 2.65	25.93 ± 3.81
MBI		
KI-BCI	33.86 ± 0.85	62.86 ± 0.90
tDCS	35.21 ± 1.84	55.00 ± 2.14
BCI-tDCS	34.79 ± 1.66	59.79 ± 2.08

Table 3.
Comparison of clinical outcomes in the groups.

approach enhanced motor performance relative to the sole tDCS intervention, no additional functional benefit was observed compared to KI–BCI used independently over the four-week treatment period. These outcomes support the potential efficacy of KI–BCI as a distinct rehabilitative intervention and suggest that further refinement of combined protocol parameters may be necessary to achieve synergistic effects.

9. Conclusion(s)

BCI training enhances upper and lower limb motor function in subacute and chronic stroke patients by inducing cortical reorganization and activating homologous premotor areas and sensorimotor cortical networks, thereby facilitating targeted motor recovery.

As a new way of control and communication, BCI has been gradually applied to clinical practice, especially in stroke patients with significant efficacy, but BCI treatment is still in its infancy, and there are still many shortcomings. The quality problems of BCI equipment mainly include the quality of brain signal acquisition in stroke patients and the long-term effectiveness of signal processing. These factors will affect the collection and application of EEG signals, thereby affecting the treatment effect. Judging from the existing research, the specific recovery mechanism of BCI in treating stroke patients and the factors affecting the effectiveness of BCI rehabilitation treatment are still unclear, including the type of injury and recovery stage of stroke patients, as well as the intensity, type, and treatment time of BCI in treating stroke patients. These uncertainties will affect the formulation of prescriptions for BCI treatment and, thus, affect the therapeutic effect. This also requires larger-scale clinical studies and further verification through imaging examinations such as fMRI. Current stroke BCIs primarily comprise of invasive and non-invasive systems. While IBCI offers superior signal fidelity through implanted hardware, it carries surgical risks, infection potential, ethical constraints, and patient acceptance barriers. Conversely, NBCI's non-invasiveness, safety, and accessibility enhance clinical adoption despite lower signal resolution. Future research must, therefore, establish the optimal efficacy-safety balance between these modalities.

Conflict of interest

The authors declare no conflict of interest.

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Beyond the Hype: Risks, Realism, and Responsibilities in Digital Twins for Alzheimer's Disease

Eva Guttmann-Flury, Jian Zhao and Mohamad Sawan

Abstract

AI-driven digital twins (DTs) promise revolutionary advances in healthcare, yet their application to Alzheimer's disease (AD) diagnostics and management remains fraught with unresolved technical and ethical dilemmas. The staggering complexity of neurodegenerative processes and intrinsic human variability challenges the very premise of creating clinically viable DTs for AD. Central to this analysis is the concept of “deep learnability”, a concept that questions whether the inherent complexity of AD can be efficiently modeled given biological constraints and data limitations. This theoretical contribution is operationalized through a practical, clinically-focused metric that requires new deep learning models to significantly outperform the best interpretable alternatives to justify their use. This work also advocates for a mandatory three-tier framework for any AD DT: (1) technical validation ensuring computational robustness; (2) biological validation confirming alignment with established biomarker and imaging data; and (3) clinical validation demonstrating tangible utility in improving patient diagnosis and outcomes. This structured approach, combined with a call for global standardization and ethical design, is essential to translate the promise of DTs into clinically viable tools.

Keywords: digital twins, Alzheimer's disease, deep learnability, validation framework, personalized medicine, ethical artificial intelligence

1. Introduction

1.1 The transformative potential of AI in medicine

The integration of artificial intelligence (AI) into healthcare is widely regarded as a paradigm shift, with substantial potential to transform medical diagnosis, treatment, and research. This optimism stems from AI's demonstrated capacity to analyze vast, complex datasets, uncover patterns, and generate insights that surpass human capabilities. Such advancements are frequently described in terms of transformative roles, such as expanding the boundaries of medical knowledge and democratizing specialized expertise [1]. There is broad anticipation that AI will significantly accelerate drug development [2], enhance patient care through

personalized treatment [3], and contribute to a more equitable healthcare system through improved resource allocation [4].

Empirical evidence supports this potential. Natural language processing models show particular promise in parsing unstructured clinical notes from electronic health records, enabling more comprehensive patient phenotyping and large-scale cohort identification [5]. In medical imaging, multiple studies demonstrate AI systems achieving performance levels comparable to human experts in well-defined diagnostic tasks. For instance, in mammography interpretation, an AI system matched the average performance of 101 radiologists in a retrospective analysis [6]. Similarly, in neuroimaging, a specialized AI system achieved 91% accuracy in including the correct diagnosis among its top three differentials, performing at levels comparable to academic neuroradiologists [7].

However, critical examination reveals important limitations that necessitate a more nuanced understanding of AI's capabilities. First, while AI systems demonstrate strong average performance, they typically do not surpass the expertise of top clinical specialists, as evidenced by the consistent outperformance of leading radiologists in comparative studies [6]. Second, current AI systems operate within constrained parameters, limited to predefined disease categories and specific imaging modalities, which contrasts sharply with the open-ended complexity of clinical practice [7]. Third, the 'black-box' nature of many advanced algorithms creates significant challenges for clinical interpretability, limiting trust and adoption in high-stakes medical decision-making [8].

Additional implementation challenges emerge beyond technical performance metrics. Algorithmic biases rooted in unrepresentative training data may exacerbate existing health disparities across demographic groups, posing a heightened risk to vulnerable populations [9]. The substantial computational resources required for model development and deployment raise environmental concerns regarding the carbon footprint of energy-intensive training processes [10]. Furthermore, the effectiveness of AI assistance shows considerable heterogeneity across clinicians, with performance benefits depending critically on both individual practitioner characteristics and model accuracy [11].

Most significantly, optimal outcomes emerge not from AI replacement of human expertise but through collaborative frameworks that leverage the complementary strengths of both. Research demonstrates that decision-referral systems, where AI handles confident classifications and refers uncertain cases to radiologists, significantly outperform either approach alone in both sensitivity and specificity metrics [12]. This suggests the necessity for personalized implementation frameworks rather than universal solutions, with careful attention to validation, bias mitigation, and environmental impact.

1.2 The Alzheimer's disease challenge

Alzheimer's disease (AD) is a progressive neurodegenerative condition, characterized by a prolonged preclinical phase where pathological changes begin 20 years or more before clinical symptoms emerge. While the classical amyloid cascade hypothesis – which places amyloid – β ($A\beta$) deposition as the central causal factor – has long dominated AD research, its validity is increasingly contested [13]. A significant body of evidence highlights inconsistencies, such as the presence of $A\beta$ plaques in cognitively normal elderly individuals and the repeated

failure of anti-amyloid therapies to slow cognitive decline in sporadic cases. This suggests that the extracellular accumulation of $A\beta$ plaques and the propagation of intracellular neurofibrillary tangles composed of τ protein may only be components of a more intricate pathological cascade, involving neuroinflammation, metabolic dysfunction, and vascular contributions [14].

This disorder exhibits remarkable heterogeneity in its progression and pathological spread. Research has identified distinct subtypes of τ deposition with different spatial trajectories: limbic-predominant, medial temporal lobe-sparing, posterior cortical, and lateral temporal patterns. These variants demonstrate divergent rates of clinical decline, with the lateral temporal pattern progressing most rapidly. Such variability also extends to amyloid deposition, neuroinflammatory activity, and symptomatic presentations, indicating that AD may constitute several pathogenic pathways rather than a single illness [15].

AD's clinical and societal impact is substantial. Epidemiological data indicate that approximately 55 million individuals worldwide currently live with dementia, with projections suggesting this number may reach 139 million by 2050. The economic burden is equally staggering, with dementia care costs estimated at USD 1.3 trillion annually worldwide, encompassing direct medical costs, long-term care expenses, and the substantial informal care provided by family members [16].

Current diagnostic approaches face multiple limitations. Standard assessment relies on a combination of cognitive evaluation, neuropsychological testing, cerebrospinal fluid biomarker analysis, and neuroimaging techniques, including Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI). However, these methods present challenges, including the invasive nature of certain procedures, variable sensitivity for early detection, and the heterogeneity of clinical presentations. Additional practical barriers include limited access to specialist care, extended waiting times for comprehensive assessment, and the frequent misinterpretation of early symptoms as normal aging [17]. These systemic and therapeutic challenges, combined with the growing prevalence and substantial economic impact, highlight the need for improved approaches to early detection, accurate prognosis, and intervention development [18].

1.3 The digital twin promise

A digital twin (DT) constitutes an advanced computational paradigm that creates and maintains a dynamic virtual representation of a physical entity through continuous data synchronization. In engineering applications, this approach facilitates comprehensive system simulation, perturbation analysis, and exploration of failure scenarios through sophisticated *in silico* experimentation. Unlike conventional machine learning models focused on specific predictive tasks, DTs aim to provide comprehensive digital replicas capable of supporting multifaceted analytical investigations across diverse domains [19].

In healthcare, this concept introduces a fundamental transformation toward personalized medicine. A medical DT is an adaptive, multiscale computational model of an individual patient that integrates multimodal health data to simulate physiological processes, predict outcomes, and optimize interventions. This methodology transcends traditional AI applications by capturing systemic complexity rather than addressing isolated clinical questions [20].

The application of DTs to AD presents particularly significant opportunities. A well-constructed AD DT would synthesize omics (e.g., genomic, transcriptomic, proteomic, metabolomic), static and dynamic neuroimaging, and longitudinal clinical data to generate patient-specific disease progression models. Such models could empower clinicians to simulate therapeutic interventions, predict treatment responses, and develop personalized management strategies that account for individual variability (**Figure 1**) [21].

Innovative biological platforms, including brain organoids, present supplementary avenues for DT enhancement. These three-dimensional cellular systems, derived from patient-specific stem cells, provide experimentally accessible models of neural tissue that can capture disease-specific phenotypes. Incorporation of such experimental systems within DT architectures may improve the representation of pathological mechanisms and intervention testing, potentially enabling more reliable prediction of clinical outcomes in AD [22].

1.4 A necessary reality check

The ambitious vision for DTs in AD must be critically evaluated against the practical and ethical constraints that currently limit their application. Initial results, while compelling, come with significant caveats. For instance, one model achieved a promising 87% (SD $\pm$ 8%) accuracy in forecasting progression to mild cognitive impairment using EEG, starkly outperforming standard biomarkers (54% $\pm$ 7%) [23]. However, these metrics are frequently derived from small-scale validation studies (N = 7 in the aforementioned study), and often lack direct benchmarks against established clinical prognostic tools.

A primary obstacle is the scalability and robustness of these models. The conceptual goal of merging multimodal data – from omics data to neuroimaging – confronts the concrete challenges of managing heterogeneous, high-dimensional,

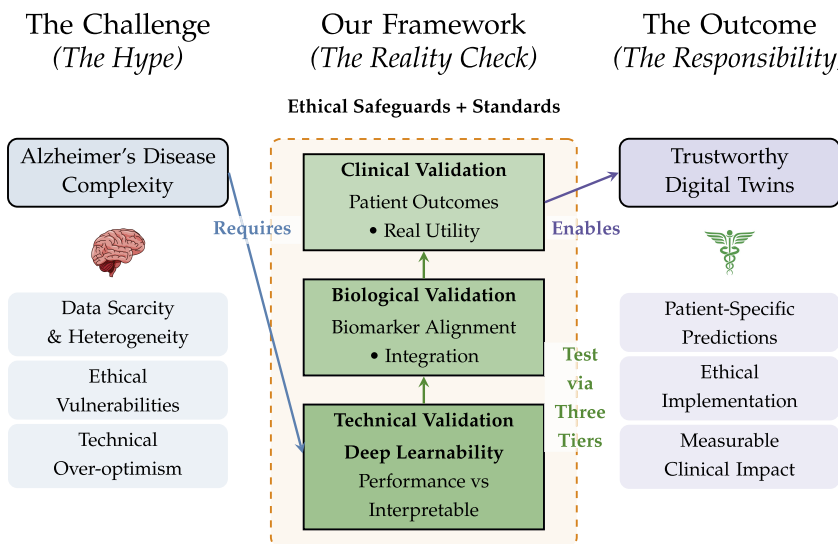


Figure 1. A conceptual framework for responsible Alzheimer's digital twins. This integrated visualization connects technical validation, ethical considerations, and clinical translation into a unified development paradigm.

evolving datasets. The substantial computational load required for model personalization and periodic updates presents a major barrier to viable integration into routine clinical practice, where efficiency is crucial [24].

Equally critical are the ethical ramifications. DTs' predictive power raises serious concerns about algorithmic bias, potentially worsening healthcare disparities if trained on non-representative data. Managing sensitive personal information requires unprecedented privacy safeguards, while the psychological impact of receiving probabilistic decline forecasts demands new ethical frameworks [25].

Consequently, the future of DT technology hinges on a rigorous validation paradigm. Its success must be measured not by isolated accuracy scores but through consistent, demonstrable utility across diverse, real-world populations. Advancing the field requires a committed focus on overcoming these technical hurdles, establishing strong ethical guidelines, and providing transparent, comparative evidence of clinical value before this innovative approach can fulfill its long-term promise.

1.5 Objectives and scope

The following analysis addresses the critical need to establish a constraint-aware, validation-driven paradigm for DT development in AD research (**Figure 2**). The primary objective centers on advancing the field from technological optimism toward a framework governed by measurable “deep learnability” – a novel concept quantifying computational models' capacity to extract and generalize clinically relevant patterns from longitudinal neurodegenerative data spanning decades of disease progression.

Specific emphasis is placed on bridging theoretical DT capabilities and clinical application by addressing three fundamental bottlenecks: mathematical intractability in modeling multiscale neurodegeneration, ethical obligations for neural data governance, and limitations stemming from sparse multimodal datasets with high intra- and inter-subject variability. Corresponding solutions will prioritize standardization protocols to ensure data comparability, ethically informed design protocols, and international standardization employing robust neurophysiological signals as reference benchmarks.

This structured approach establishes operational boundaries for DT innovation while ensuring alignment with ethical imperatives and clinical realities. The following sections will systematically examine how DT technology can be specifically applied to AD, formalize metrics for deep learnability, and advance validation methodologies using neurophysiological anchors to mediate between engineering models and biological complexity.

2. DT for Alzheimer's disease

2.1 Origins and mathematical foundations

The DT concept originates from the simulation-driven world of industrial engineering. Its philosophical roots are famously traced to NASA's Apollo program, where physical systems on Earth mirrored the spacecraft's state, enabling critical diagnostics and simulations [26]. Formally defined in manufacturing, a DT is

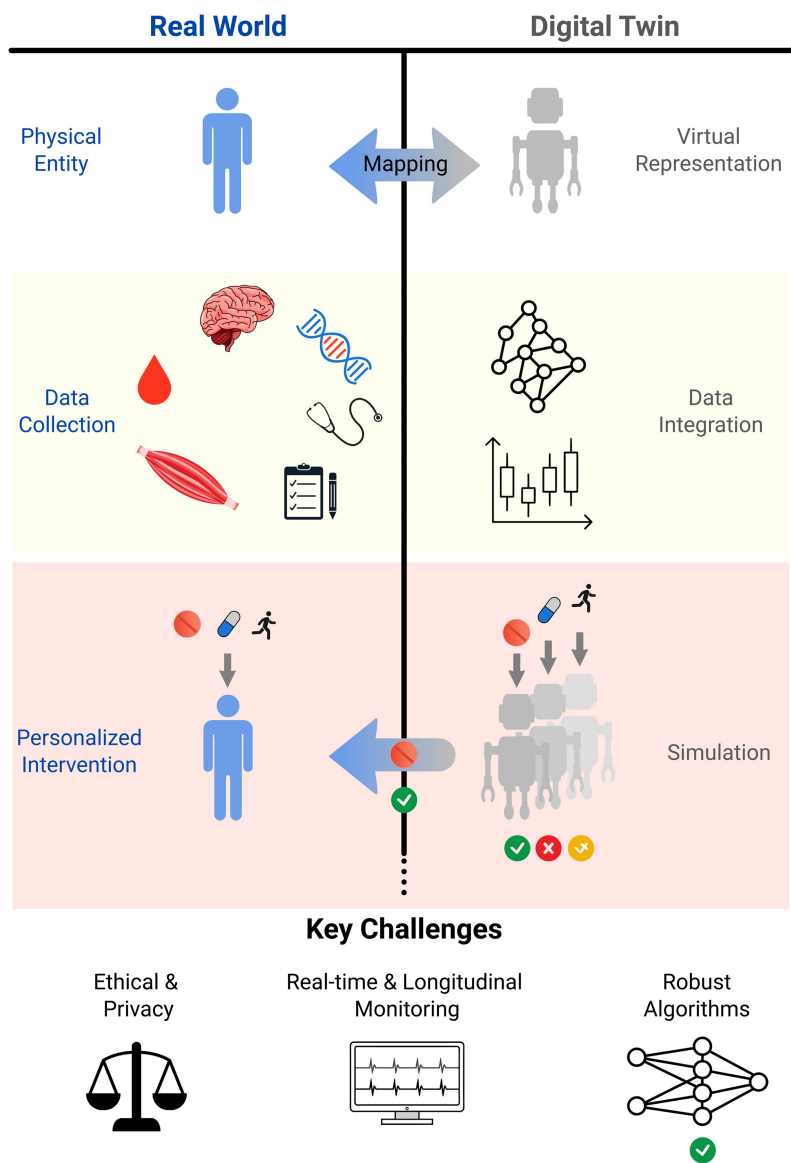


Figure 2. Conceptual overview of a medical digital twin. The framework bridges the physical and digital worlds to enable personalized medicine through simulation, highlighting three major implementation challenges.

a dynamic virtual replica of a physical asset, characterized by sustained bidirectional information flow for simulation, prediction, and optimization [27].

Figure 3 illustrates the architectural translation of this paradigm to AD. When applied to healthcare, the DT framework enables three core functions: *longitudinal data assimilation*, which maintains alignment between the physical patient and their virtual counterpart through periodic clinical assessments; *anticipatory capacity*, which uses the model’s internal mechanics to emulate future states of disease progression across clinically relevant timescales; and *operational agency*, where

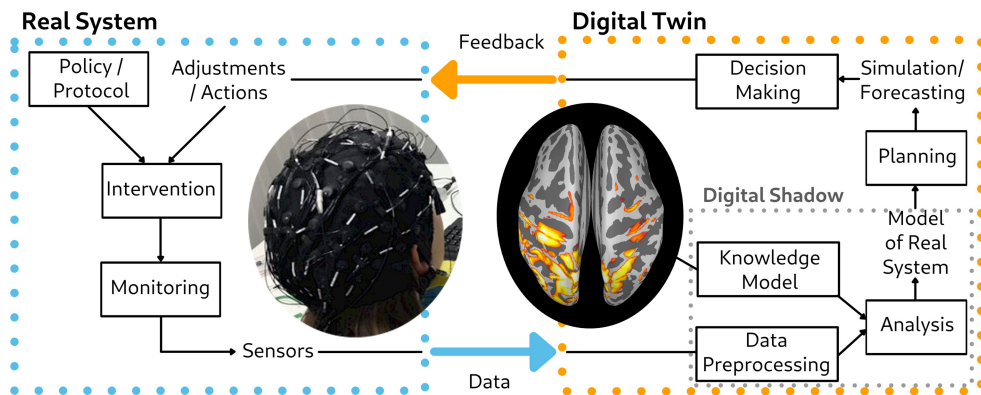


Figure 3.
 Real system and digital twin global architecture for healthcare in general and Alzheimer's disease in particular.

insights from virtual experimentation directly inform real-world clinical interventions, such as optimizing therapeutic strategies or drug dosage.

The foundational first step is constructing an accurate digital shadow – a high-fidelity, data-rich model that passively reflects the biological state. This transformation involves fundamental trade-offs: the richness of continuous neurological processes must be reduced to discrete data points, while the complexity of Alzheimer's pathology is simplified into model-compatible parameters. Each data source, from neuroimaging to genomic profiles, captures only a partial aspect of this continuum, filtered through the limitations of measurement technologies and sampling frequencies. The resulting shadow is necessarily an imperfect reconstruction, shaped as much by what is technically measurable as by what is biologically significant.

The transition from a passive digital shadow to an active DT then necessitates integrating dynamics across spatial (molecular to organ) and temporal (seconds to decades) scales. The core challenge is to formalize the disease's progression – driven by the interplay of proteinopathy and/or metabolopathy, neurodegeneration, and cognitive decline – into a computationally tractable model that can be personalized with individual patient data. The mathematical approaches employed generally fall into three complementary categories, each tied to a specific hypothesis about disease mechanisms.

2.1.1 Mechanistic (bottom-up) models

Rooted in systems biology and physics, this approach uses differential equations to formalize explicit biological hypotheses. A common strategy couples the aggregation and diffusion of $A\beta$ with the progression of neuronal dysfunction, frequently described by Smoluchowski-type equations [28]:

$$\partial_t u_m = D_m \nabla^2 u_m + \left[\frac{1}{2} \sum_{j=1}^{m-1} K_{j, m-j} u_j u_{m-j} - u_m \sum_{j=1}^N K_{m, j} u_j \right] - \lambda_m u_m \quad (1)$$

where $u_m(\mathbf{x}, t)$ is the concentration of $A\beta$ aggregates of size m , D_m is a diffusion coefficient, K_{ij} are coagulation rates, and λ_m is a clearance rate. This formulation is typically coupled to an equation for neuronal health, structured by a continuous

“damage” variable. While powerful for testing the “Protein Cascade Hypothesis,” such detailed mechanistic approaches face significant challenges in parameter identifiability and computational cost [29].

2.1.2 Network-based (top-down) models

In contrast to mechanistic details, this category prioritizes the architectural connectivity of the brain. The “Network Diffusion Hypothesis” posits that pathology spreads along the brain’s structural connectome. A foundational model describes the propagation of a pathological agent [30]:

$$\frac{d\mathbf{y}(t)}{dt} = -\beta\mathbf{L}\mathbf{y}(t) \quad (2)$$

where $\mathbf{y}(t)$ is a vector representing pathology burden in different brain regions, β is the rate constant of network diffusion, and $\mathbf{L}$ is the graph Laplacian matrix of the structural connectome. The solution, $\mathbf{y}(t) = e^{-\beta\mathbf{L}t}\mathbf{y}(0)$, predicts the spatiotemporal pattern of atrophy based on network topology. These models are powerful for predicting imaging-based progression but are less directly tied to molecular mechanisms.

2.1.3 Data-driven (phenomenological) models

Diverging from hypothesis-driven constructs, this final class leverages machine learning and statistical inference to learn progression patterns directly from large multimodal datasets. The learning process for many such models, including generative architectures like Conditional Restricted Boltzmann Machines (CRBMs) [31], can be framed as an optimization problem. The goal is to learn a set of parameters θ that minimize the difference between the model’s predictions and the observed patient data. This often involves maximizing the log-likelihood of the observed data $\mathbf{v}$ (e.g., clinical scores) given the hidden states $\mathbf{h}$ and conditional data $\mathbf{c}$ (e.g., patient demographics, baseline biomarkers):

$$\mathcal{L}(\theta) = \sum_{n=1}^N \log P(\mathbf{v}^{(n)} | \mathbf{c}^{(n)}; \theta) = \sum_{n=1}^N \log \sum_{\mathbf{h}} e^{-E(\mathbf{v}^{(n)}, \mathbf{h}, \mathbf{c}^{(n)})} - \log Z(\mathbf{c}^{(n)}) \quad (3)$$

where $E(\mathbf{v}, \mathbf{h}, \mathbf{c})$ is an energy function defining the interactions between visible units $\mathbf{v}$, hidden units $\mathbf{h}$, and conditional units $\mathbf{c}$; $Z(\mathbf{c})$ is the partition function; and N is the number of training samples. The parameters θ are typically learned approximately using contrastive divergence. These models excel at prediction and generating virtual patient trajectories, but their phenomenological nature can render them “black boxes,” offering limited mechanistic insight into the underlying disease processes.

2.1.4 Surrogate modeling approaches

Distinct from data-driven models that learn patterns directly from patient observations, surrogate modeling creates efficient approximations of existing physiological simulations. While data-driven approaches discover relationships from clinical data, surrogate techniques emulate the input-output behavior of established models to accelerate their execution.

Methods, including Gaussian processes, neural network emulators, and reduced-order modeling, enable practical parameter exploration and near real-time prediction essential for clinical deployment, without embodying new biological insights about disease mechanisms. Multi-fidelity strategies leverage relationships between inexpensive approximations and their physiologically-grounded counterparts to maintain predictive accuracy when comprehensive simulations are infeasible [32].

The essential distinction lies in their fundamental purpose: while physiological models seek to understand disease mechanisms, surrogate approaches prioritize performance optimization. This operational efficiency necessitates careful validation to ensure these proxies preserve the dynamic behaviors captured by their physiological foundations in clinical DT implementations.

2.2 Current diagnosis directions

Formalized by the National Institute on Aging and Alzheimer's Association (NIA-AA) research framework, the contemporary diagnostic process prioritizes the detection of AD pathophysiology in its preclinical and prodromal stages, often years or even decades before the onset of overt clinical dementia. The core principle is that AD is defined by its underlying biology – specifically, the presence of amyloid- β ($A\beta$) plaques and neurofibrillary τ tangles – rather than by the resulting clinical symptoms [33]. The criteria introduce a biomarker categorization that distinguishes between:

- **Core 1 biomarkers:** Early-changing biomarkers that are sufficient for diagnosis, including:
 - Amyloid positron emission tomography (PET)
 - Cerebrospinal fluid (CSF) biomarkers
 - Plasma biomarkers (especially phosphorylated τ -217)
- **Core 2 biomarkers:** Later-changing biomarkers (e.g., biofluid and τ PET) used for staging and prognosticating, but not standalone diagnosis.

Clinical evaluation relies on a combination of interviews, questionnaires, and cognitive tests. Commonly employed instruments include the Mini-Mental State Examination (MMSE), the Montreal Cognitive Assessment (MoCA), and the Mini-Cog. The MoCA is recognized for its higher sensitivity in detecting mild cognitive deficits and early-stage AD compared to the MMSE. For a more detailed neuropsychological assessment, tools like the Rey Auditory Verbal Learning Test (RAVLT) are used to evaluate verbal memory and learning, serving as effective early markers for AD in individuals with memory complaints. Furthermore, the Clinical Dementia Rating Scale, particularly the Sum of Boxes (CDR-SB), has demonstrated excellent predictive value for detecting the onset of dementia in non-demented individuals and is sensitive to disease progression across different severity levels [34].

To account for the heterogeneity and dynamic progression of AD pathology, interdisciplinary efforts integrating neurology, data science, and clinical medicine are increasingly focused on multimodal approaches. These combine molecular biomarkers, structural and functional neuroimaging (e.g., structural and functional MRI), and detailed cognitive assessments to capture complementary aspects of the disease. Such integration aims to improve early detection, refine staging, and enable more personalized prognostic assessments. **Table 1** presents classification performance achieved when such multimodal datasets are analyzed with contemporary machine learning pipelines but must be interpreted in light of limited sample sizes and uneven external validation [35].

Sensitivity measures the proportion of correctly identified positive cases (e.g., true AD patients identified as AD), and specificity measures the proportion of correctly identified negative cases (e.g., true normal controls (NC) identified as NC). The high values for the AD vs. NC task indicate that the model is excellent at separating clear disease states from healthy aging. The more moderate values for earlier, subtler distinctions, like Progressive MCI vs. Stable MCI, reflect the inherent difficulty of predicting conversion within a high-risk group – a task where even expert clinicians struggle.

2.3 Core implementation challenges

The transition from established diagnostic frameworks to dynamic DT models reveals several fundamental implementation challenges specific to AD. While current approaches provide valuable static snapshots of the disease state, they also highlight the limitations that comprehensive computational models must overcome to deliver meaningful clinical advancements.

2.3.1 Temporal scale mismatch

AD’s decades-long progression creates a fundamental temporal disconnect between pathological processes and clinical observation. While biomarkers can identify disease presence, they provide limited insight into the continuous biological evolution occurring between sparse clinical assessments. This scale mismatch challenges DT to interpolate and extrapolate disease trajectories from temporally limited data, requiring models that can bridge molecular timescales with clinical timescales while maintaining predictive accuracy for near-term clinical decisions [36].

Classification task	Pooled sensitivity (95% CI)	Pooled specificity (95% CI)
AD vs. NC	94.60% (90.76–96.89%)	93.49% (91.60–94.90%)
MCI vs. NC	83.77% (78.87–87.71%)	79.16% (70.97–87.71%)
pMCI vs. sMCI	80.41% (74.73–85.06%)	81.44% (76.32–85.66%)
EMCI vs. NC	86.63% (82.43–89.95%)	85.68% (81.62–88.96%)

Note: AD = Alzheimer’s disease; NC = normal control; MCI = mild cognitive impairment; pMCI = progressive MCI; sMCI = stable MCI; EMCI = early MCI.

Table 1.
Summary of classification performance using multimodal neuroimaging and machine learning for Alzheimer’s disease staging.

2.3.2 Pathological heterogeneity integration

The heterogeneity observed in diagnostic classifications – ranging from distinct τ spreading patterns to varied amyloid deposition profiles – must be comprehensively integrated into DT architectures. Rather than treating this diversity as noise, effective DT must capture the spectrum of pathological manifestations and their implications for individual progression trajectories. This requires moving beyond population-level averages to models that can accommodate the complex interplay between different pathological processes and their variable clinical expressions across individuals [37].

Critically, while current diagnostics focus heavily on “core” disease-defining pathologies ($A\beta$, τ), accurately modeling the differential rates of clinical decline may require DTs to also incorporate key prognostic biomarkers (i.e., measures that predict the likely pace and severity of future decline). These could include measures of neuroinflammation, immune system function, metabolic dysregulation, synaptic integrity, and vascular health. Such systems may not merely respond to the primary pathology but could actively modify its clinical expression, potentially serving as key explanatory variables for why two patients with similar amyloid and τ burdens can experience dramatically different trajectories.

2.3.3 Multi-scale causal inference

Perhaps the most significant challenge lies in establishing causal relationships across the biological hierarchy. Current diagnostics identify associations but provide limited insight into the causal mechanisms linking molecular events to network dysfunction and cognitive decline. DTs must overcome this limitation by integrating knowledge from protein aggregation dynamics through neural circuit alterations to emergent cognitive symptoms, while distinguishing driving pathologies from compensatory adaptations [38].

3. The concept of deep learnability

3.1 The staggering complexity of the brain

The application of artificial intelligence in neuroscience, particularly through DTs for AD, confronts profound stochastic and computational challenges that question the very feasibility of creating accurate digital replicas of neural systems. These challenges stem from the brain's extraordinary biological complexity, which operates on principles fundamentally different from the physical systems where DTs have demonstrated success.

To appreciate these challenges, consider fundamental probability principles: as a coin is tossed repeatedly, the observed probability approaches the theoretical value of 0.5, and similarly, a die's specific configuration converges to its expected value (e.g., 1/6 for a six-faced die) with sufficient trials. These systems represent relatively low computational complexity where outcomes can be predicted with increasing accuracy given adequate data. However, when scaling to complex artificial systems like Large Language Models (LLMs) with billions of parameters, the probability of

any specific configuration becomes astronomically small – approximately 2.5×10^{-9} for models with 4 billion parameters and 5.7×10^{-11} for those with 175 billion parameters.

The human brain presents challenges orders of magnitude greater than even the most advanced AI models. With an estimated 86 billion neurons, each receiving between 1,700 and 30,000 inhibitory and excitatory inputs (particularly pyramidal cells), the brain constitutes a network of connections staggering in its potential configurations [39, 40]. Moreover, neural activity is not static but dynamically influenced by myriad environmental and physiological factors – including fatigue, hunger, and temperature – that vary across sessions. This dynamic, multifaceted nature raises a fundamental question: Is it feasible to use AI for neuroscience, particularly for a condition as complex as AD?

3.2 Defining “deep learnability”

This question necessitates the formalization of “deep learnability” – a novel concept grounded in statistical learning theory (SLT) to assess the feasibility and limits of computational modeling. SLT frames the learning problem around risk optimization, where the objective is to identify a function that reduces the expected error on new, unseen data, moving beyond simple memorization of training examples. Crucially, SLT provides probabilistic upper bounds on generalization error, offering guarantees of the form: given a finite dataset of size N and a model of complexity C , the error on new data will be less than X with probability Y [41].

Within this framework, we define deep learnability as *the quantifiable capacity of a machine learning model to extract, represent, and generalize the underlying governing principles of a complex system from high-dimensional, noisy, and often sparse observational data*. Its value is determined by benchmarking performance against the best available non-deep learning model. For systems of extraordinary complexity, like the human brain and AD pathology, this presents a fundamental challenge. The combinatorial explosion of possible neural states and pathological features creates a space where comprehensive deep learnability across the entire system may be theoretically impossible.

This limitation, however, doesn’t preclude achieving deep learnability within constrained subdomains. Well-defined, smaller problem spaces (e.g., specific biomarker dynamics, localized network alterations, or particular cognitive domains) exhibit higher inherent deep learnability due to their reduced complexity and improved signal-to-noise ratio (SNR). In high-dimensional biological systems, features may act as mutual confounders – while not inherently noise, the signal of one variable can obscure another when analyzed concurrently. By isolating subdomains, the relative SNR for specific signals is enhanced, as independent sources of variation that are unrelated to the feature of interest are minimized.

These learnable subdomains can then be integrated through meta-learning frameworks, where a higher-level model synthesizes predictions from specialized sub-models. Deep learnability thus exists on a spectrum shaped by several key factors central to SLT’s bias-variance trade-off:

- The SNR of the input data within a defined subdomain.
- The complexity and non-linearity of the system’s dynamics.

- The temporal and spatial resolution of the measurements.
- The quantity and diversity of available training data.
- The architecture and explainability of the learning model itself.
- The inherent biological and clinical variabilities of the modeled system.

3.3 Operationalizing deep learnability for clinical translation

From a theoretical perspective, we propose that the deep learnability ($\mathcal{DL}$) of a system for a given modeling task can be framed by the achievable lower bound of the prediction error relative to the best-performing interpretable model. A potential formalization involves the estimation of the excess risk or generalization error. Let $R(f)$ be the expected risk (theoretical average error) of a predictive function f (e.g., forecasting disease progression) and $R(f^*)$ be the Bayes error rate (i.e., the irreducible minimum error achievable by any model due to inherent system stochasticity), the deep learnability can be inversely related to the minimal excess risk achievable:

$$\mathcal{DL} \propto \frac{\rho_{\text{non-DL}}}{\inf_{f \in \mathcal{F}} [R(f) - R(f^*)] + \epsilon} \quad (4)$$

where $\mathcal{F}$ is the hypothesis space of our model class (e.g., deep neural networks), ϵ represents an irreducible error term stemming from the inherent stochasticity of the system, and $\rho_{\text{non-DL}}$ is the error corresponding to the fixed performance benchmark established by the best interpretable model (i.e., not a deep learning one). The excess risk $[R(f) - R(f^*)]$ decomposes into approximation error (from limiting our search to $\mathcal{F}$ instead of all possible functions) and estimation error (from finite data to learn from).

This definition is analogous to how SNR quantifies a signal's recoverability from noise. However, while SNR measures the purity of the observable signal itself, deep learnability encompasses the broader challenge of extracting meaningful representations from that signal through computational learning.

Given the critical nature of medical decision-making, there exists a strong preference for models that are not only accurate but also clinically interpretable. This preference stems from the necessity for physicians to understand the reasoning behind predictions, particularly in high-stakes scenarios involving neurodegenerative diseases. For clinical applications, we introduce a practical deep learnability metric ($\mathcal{DL}_p$) that should be evaluated relative to the best-performing interpretable model:

$$\mathcal{DL}_p = \frac{\text{Performance}_{\text{DL}}}{\text{Performance}_{\text{non-DL}}} \quad (5)$$

Here, Performance is a clinically relevant metric, such as the area under the receiver operating characteristic curve (AUC-ROC) for classification tasks, the concordance index (C-index) for survival analysis, or the negative mean squared error for continuous outcome prediction. The specific metric must be chosen based on the clinical question at hand.

This formulation recognizes that when deep learning models achieve significantly better performance, their clinical utility may outweigh interpretability concerns, particularly in scenarios where accurate predictions directly impact patient outcomes. The $\mathcal{DL}_p$ ratio must exceed a threshold value greater than 1 to justify the adoption of more complex models, with the exact threshold dependent on the specific clinical application and the associated risk tolerance.

4. A framework for responsible development: Validation, ethics, and standardization

4.1 Validation-first paradigm

Establishing rigorous verification protocols requires a structured methodology that progresses from mathematical and/or heuristic foundations to clinical implementation. The initial phase must ensure computational robustness by verifying numerical stability, conducting comprehensive sensitivity analyses of key parameters, and stress-testing models under extreme biological scenarios. These technical assessments guarantee that model architectures can adequately handle the complex, non-linear dynamics characteristic of neurodegenerative processes while maintaining performance consistency across the spectrum of AD pathology, from preclinical stages to advanced dementia [42].

The second tier addresses biological plausibility through multimodal benchmarking. DTs must align with established biomarker trajectories – including amyloid-PET, CSF profiles, MRI atrophy measures, and relevant prognostic biomarkers that modify disease expression. This process requires longitudinal data spanning clinically relevant timescales, with particular emphasis on critical transition periods between disease stages. The assessment framework must account for AD's inherent heterogeneity by employing performance metrics stratified across biological subtypes and demographic variables, ensuring model reliability across diverse patient populations [43].

The final validation tier assesses clinical integration and utility through prospective observational studies and controlled trials. This phase moves beyond mere predictive accuracy to evaluate actual clinical impact, including effects on diagnostic confidence, therapeutic decision-making, and patient outcomes. Crucially, these studies should examine how clinicians interpret and utilize DT outputs, ensuring these tools augment rather than replace expert judgment. The preservation of clinical expertise remains essential, as over-reliance on algorithmic predictions could potentially undermine the diagnostic skills and critical thinking capabilities necessary for managing complex cases [44].

4.2 Ethically grounded design protocols

The development of AD DTs necessitates ethical frameworks that address the unique vulnerabilities of this patient population. Informed consent processes require fundamental adaptation to accommodate cognitive decline, incorporating dynamic consent mechanisms that allow for ongoing authorization and withdrawal as the disease progresses. This approach demands the development of tiered consent

frameworks that actively engage both patients and caregivers while respecting evolving decision-making capacity and preferences [45].

Data governance must implement robust protections for neural and genomic information, recognizing the exceptional sensitivity of brain-related data. Privacy-preserving technologies, including federated learning and differential privacy, should be employed to minimize data exposure while maintaining analytical utility. Concurrently, protocols must be established for the ethical management of incidental findings and unexpected predictions, particularly those with significant psychological implications for patients and families [46].

Algorithmic fairness necessitates proactive representation across diverse populations. Development cohorts must adequately include ethnic, genetic, and socioeconomic groups to ensure equitable global performance. Continuous monitoring for discriminatory outcomes, with mechanisms for bias detection and mitigation, should be implemented throughout the model lifecycle [47].

4.3 Global standardization framework

International collaboration is essential for establishing standardized protocols that ensure interoperability and reproducibility across healthcare systems. This effort begins with harmonized data acquisition standards that specify minimum requirements for multimodal data collection, including imaging protocols, biomarker assays, and clinical assessment tools. Standardization should extend to data formatting, annotation practices, and metadata specifications to enable meaningful cross-study comparisons and aggregation [48].

Reference benchmarks must be established using well-characterized biological signals with established clinical correlates. These should include validated neurophysiological markers, molecular biomarkers, and imaging phenotypes that demonstrate consistent properties across populations and measurement platforms. Such benchmarks anchor DT predictions to biological reality, enabling continuous performance assessment and model refinement [49].

Regulatory harmonization efforts should develop DT-specific evaluation frameworks that address their dynamic, patient-specific nature. This requires adapting existing medical device regulations for evolving learning systems while maintaining rigorous safety standards. International consensus on validation requirements, update protocols, and performance monitoring will facilitate global development while ensuring patient protection across jurisdictions [50].

5. Discussion and future directions

The development of clinically useful DTs for AD requires a shift from broad ambition to targeted, practical development. The framework presented here, based on deep learnability, establishes the necessary principles for this work. Future progress will depend on advancing several key areas that connect computational models to real-world clinical value.

A critical next step is the creation of granularity-based modeling architectures. Rather than building highly complex, one-size-fits-all models, future systems should dynamically adjust their level of detail based on the specific clinical question and available data. A model for predicting long-term disease risk and probable speed of

progression, informed by prognostic biomarkers, does not need the same biological resolution as one designed to simulate drug effects. This flexible structure is essential for managing computational costs while ensuring scientific accuracy and clinical relevance.

Furthermore, to provide more than just correlations, the next generation of DTs must integrate causal discovery frameworks. Current models often identify statistical associations without proving cause and effect. Integrating techniques that can infer causal relationships from longitudinal data would allow DTs to identify true disease drivers, separate from secondary effects or compensatory changes. This would significantly improve their utility in identifying treatment targets and personalizing patient care.

Finally, for clinical adoption, DTs must be designed to quantify and communicate uncertainty. Model outputs should not be single predictions but rather probability distributions that express confidence levels based on data quality, model reliability, and biological variation. These uncertainty estimates must be built into clinical decision support systems, clarifying when a model's output is robust enough to inform action and when it should be overruled by clinical judgment. This is a fundamental requirement for safety and ethical implementation.

6. Conclusion

This chapter introduces a conceptual framework for advancing DTs in AD research, centered on the novel concept of deep learnability. This metric provides a rigorous approach to evaluate whether complex computational models offer sufficient clinical advantage over established interpretable methods to justify their implementation, thereby shifting focus from technical feasibility to practical clinical benefit.

The proposed multi-tiered validation paradigm integrates this theoretical foundation with ethical design principles, requiring potential DTs to demonstrate biological plausibility, clinical utility, and operational safety alongside statistical performance. The incorporation of dynamic consent protocols, bias mitigation strategies, and robust data governance ensures alignment with patient welfare priorities throughout development.

This critical framework addresses a pressing need in the field as medical AI advances rapidly. By establishing clear evaluation benchmarks and development boundaries, this work provides essential guidance for creating targeted, trustworthy digital tools that can meaningfully contribute to personalized prognosis and therapeutic strategies in AD care, while avoiding the pitfalls of poorly validated or ethically problematic applications.

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Chapter 6

Brain Interfacing, as a Key for Improving Human–technology Integration, Cases and Implementations

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Abstract

The rapid evolution of global interconnection systems has catalyzed a paradigm shift in which the convergence of human cognition and technology is no longer a distant vision, but a tangible research priority. This integration offers unprecedented opportunities to enhance human comfort, extend capabilities, and improve safety in daily life. While current electroencephalogram (EEG) hardware presents ergonomic challenges regarding portability and user comfort, the methodologies for signal acquisition and processing have advanced sufficiently to model robust applications today, paving the way for the miniaturized devices of tomorrow. With this perspective, this chapter explores three critical research avenues illustrating how brain monitoring can redefine Human-Machine Interaction (HMI) with minimal intrusion. First, we examine the origins and applications of Advanced Driver Monitoring for Assistance Systems (ADMAS), analyzing how neuro-sensing can mitigate accidents by detecting driver fatigue and distraction. Second, the chapter addresses Ambient Assisted Living (AAL) through the lens of “Emotional Domotics” (ED), proposing responsive environments that dynamically adapt to the user’s affective state in real-time to maximize psychological well-being. Third, we present assistive systems designed for the elderly, specifically focusing on continuous monitoring and active support mechanisms during progressive stages of cognitive decline. By detailing the theoretical foundations and reported case studies of these lines, this work demonstrates that despite current hardware limitations, intelligent signal processing can create a symbiotic relationship between humans and technology. Ultimately, this chapter provides a roadmap for developing future neuro-technological tools that are not only functional but also deeply empathetic to the complexities of human experience.

Keywords: ambient assisted living, ADAS, care systems, user monitoring, aging, mobility

1. Introduction

The advent of interoperation and interconnection systems in our current world has led various institutions and enterprises to dream and focus on the development of possibilities where humans and technology merge as one. Among the concepts in recent years that have driven the revolution and focus on new technologies and research lines for system integrations, we can find terms like Cyber-Physical Systems (CPS), Industry 4.0, Digital Twins (DT), collaborative robots, among others. Most of these topics have allowed researchers to explore the link between the virtual and simulated world with the physical world, leading to advances such as predictive and smart maintenance and optimized testing protocols. However, in this automation system, there is still an area of opportunity to further empower technological advancements. This area of opportunity is the integration and connection of the human in the loop. This possibility is one of the many areas of opportunity that emerged thanks to the development of Brain-Computer Interfaces (BCI). In this chapter, we will first explore some of the basic concepts of what BCI is and the technologies that are revolutionizing the world. After this brief exploration, we will present and propose three areas of opportunity with concrete cases for the development of BCI-based systems with applications in mobility, health, and home automation. In these cases, we will first explore the origins of the projects and present their evolution route. At the end of each test case, we will explain how the integration of BCI is allowing or will allow further advancement of the corresponding research line. Finally, we will close the chapter with a brief discussion of potential focus areas for further development of BCI-based advancements.

The term BCI refers to an emerging technology that allows communication and interaction between the brain and a computer [1, 2]. Such interaction can be achieved through the use of electronic systems, either connected directly to the brain or worn on the head of the users [3, 4]. BCI links the brain's electrical activity with external physical elements to enable interaction with physical systems, even without the need for physical action or muscular activation [2]. The term BCI, first proposed by the author Vidal in 1973 [5], has since been a source of interest due to its potential implementation in various areas. Different authors have proposed the division of BCI implementations depending on the implementation focus, while others have based it on the related industry. An example of the latter is the one proposed by Maiseli et al. Maiseli proposed a classification based on the industry impacted by the application of the technology, with the following categories: Gaming and entertainment, security and authentication, healthcare, education, advertisement and neuromarketing, and neuroergonomics [1]. An example of the classification based on implementation areas is the one proposed by Howard, who suggests four categories: communication, independence, entertainment, and workplace [3].

The structure of this document is illustrated in the graphical abstract in **Figure 1**. We will present an introduction to BCI systems and implementations, analyzing their origins and some research trends in recent years. Following this, we will explore implementations beyond purely biomedical applications, and we will proceed by presenting three case studies that summarize the research lines in driver monitoring, smart homes, and elder and dementia care. After this, we will present a brief conclusion on the potential areas of opportunity and impact that the evolution of BCI technology is creating.

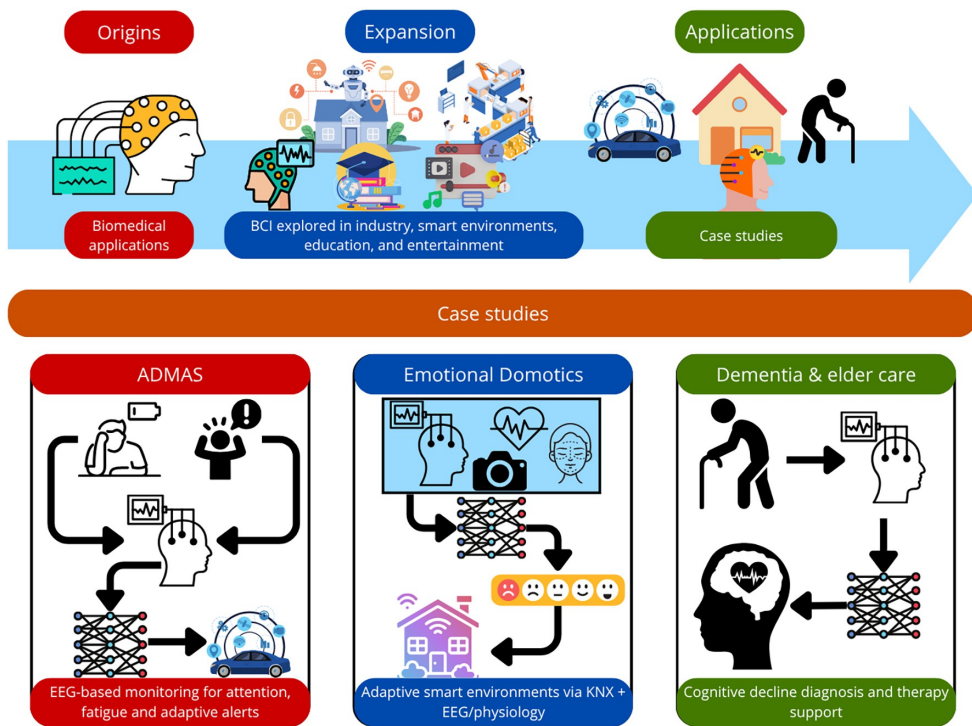


Figure 1.
 Graphical abstract.

2. BCI beyond biomedical applications

As previously mentioned, the improvement in technology accessibility for the development of sensors and computers has allowed the exploration and implementation of BCIs beyond the medical field. In this section, we will explore some of these implementations and the technologies and trends that have led to such fusion.

2.1 Industrial environment implementation

The first area of implementation that we will explore is the industrial and manufacturing sector. In this industry, we can identify three key concepts that are impacting the current technological or industrial revolution: Industry 4.0, CPS, and the Internet of Things (IoT). Industry 4.0, as summarized by Xu et al., consists of the integration of massively deployed smart and networking technologies in an industrial production and manufacturing setting, with the objective of improving the control, automation, and reliability of industrial systems [6]. In these settings, the automation, monitoring, and analysis of large amounts of data are key for the improvement of quality systems and the minimization of production delays. The implementation of large processing and monitoring systems has enabled the development of the second key concept, CPS. The term CPS was coined by Helen Gill at the National Science Foundation in the U.S. to refer to the integration of computation with physical processes and denotes the integration of computational

and physical systems [7, 8]. This embedding of physical and computational systems allows ubiquitous monitoring of the production and state of industrial systems while enabling the systems to provide follow-up and integrate smart monitoring systems to predict potential failures or deviations in the normal operation of the setting. However, the precision of the data and optimization can be affected by the quality and efficiency of data transmission and communication. This leads us to the third concept, IoT. IoT refers to the integration of sensors and processors interconnected for a constant exchange and integration of information from various sources [9]. This interconnection facilitates the deployment of monitoring strategies based on Big Data and machine learning techniques. These three concepts, as we can see, integrate the use of data exchange and the emulation of physical and virtual twins for the understanding and monitoring of industrial systems. However, traditional CPS focuses only on Machine-to-Machine or Machine-to-Infrastructure communication. One aspect that tends to be omitted or forgotten is the operator – the human factor in the industrial setting. It is in this area where BCI technologies create an area of opportunity. By integrating human monitoring into data collection, we may be able to understand and further prevent danger to the user. BCI can function as a monitoring system to detect anomalous conditions or declines in the user due to fatigue or other external factors, allowing an efficient response prior to an increase in risk to the user. One such approach has been proposed by Venthur et al. [10]. Just as BCI can be used for monitoring the state of the worker, it can also be used as a control element for operating machines in cases of partial impediments. However, as such implementation can be considered more of a biomedical approach, it is deemed beyond the scope of this Section.

2.2 Neuroergonomics and smart environments

Smart environments, for the current document, refer to the integration of sensors and actuators for the monitoring and control of any inhabitable space. These spaces include homes, workplaces, and transportation environments. In this section, we will explore general terminology and some examples; however, we will include an in-depth analysis of two of the three case studies to be presented in further sections.

Smart environments are those intervened inhabitable spaces, whose intervention through technological means, including sensing, actuating, and communication, has the intention of improving safety, luxury, and physiological control in humans' daily lives, as proposed by Abdulkader [11]. Just as in the case of industrial environment implementation, one of the key concepts is IoT. One of the largest challenges of integration in inhabitable spaces is the variety and diversification of home automation systems. This challenge can be addressed by the integration of standardized technologies. One such example is the international standard KNX, which has been explored and implemented in home environments such as elder care facilities [12], vehicles such as trains [13], and work environments [14], among others. Given the need for ease of integration of technologies in the home environment, one of the approaches that we can find focuses on the development of Universal Plug and Play technologies and networking, such as the one proposed by Lin et al. [15]. In their proposal, they suggest the connection via BCI of the user with the control and communication system of the house to control house appliances based on changes in the user's cognitive state. One of the limitations of this approach may be the kind of interface being used and, depending on the interface, the possible

noise in the signal. In their approach, Lin's team used a wireless communication system to reduce bulkiness and movement impediments while analyzing attention and drowsiness. Another such implementation, which will be reflected on, is the Emotional Domotics (ED) research, which will be explored further in the study cases. Given the high complexity of the data and stimuli sources while integrating the BCI as an element for monitoring the user, proposals such as the integration of context-awareness have been suggested to expand the reach and pervasiveness of ambient intelligence systems, just as proposed by Navarro et al. [16].

In the same manner that living environments can be intervened, one of the areas of opportunity is the intervention of mobile environments, which is the case with vehicles. In this respect, we can have two kinds of participants in the vehicle. The first one is the driver, whose attention and interaction are key for optimal and safe control. The second participant is the passenger, whose comfort is necessary for the duration of the trip.

In the case of the driver, the focus is on the detection of distraction and fatigue, which are two of the key factors that contribute to traffic accidents. Analyzing the state of the driver presents various challenges; among them, we can find the need for the user to have continuous movement to inspect the road, activate the control elements on the vehicle, and be subjected to accelerations, both positive and negative, during operation. Among the strategies used for monitoring the driver, some proposals have included the use of EEG for fatigue detection, such as the case of the proposal by Wang et al. [17]. Others have used or proposed activity and physiological monitoring, such as Schwarz et al. [18]. Some have combined EEG and ECG for driver state monitoring, such as the case of [19], while others integrate multiple data analyses to understand the context and actions of the driver, either by monitoring the driver's actions through computer vision, as proposed by Sarla et al. [20], or the commands introduced by the user. This approach has initially been addressed as a simulation by [21]. An in-depth analysis of the transition of the research line of driver monitoring will be further explored in the test case of ADMAS [22].

Even though we previously mentioned that the driving scenario may contain two main situations for the human – being the position of driver and passenger – it is important to mention that advances in recent trends and technologies have led to a third scenario, in which the human may be considered a passenger but is required to be available to respond as necessary to take control of the vehicle. Such is the scenario derived from the development and evolution of Autonomous Vehicles (AV). This technology presents various advantages that make it desirable, such as the promise of cost-effective travel and reduced traffic congestion, along with long-term effects like environmental benefits and accident prevention by mitigating human errors [23]. However, several challenges must be addressed before AV systems can be integrated into our daily lives, with one critical aspect being user acceptance of these emerging technologies [24]. Nurturing the necessary trust in the vehicle for users to adopt such technology requires researchers to develop and integrate tools that allow the understanding and capture of the various possible scenarios that the driver may experience during their driving. This kind of analysis, usually referred to as User Experience (UX) and defined by the ISO 9241–210 [25], emphasizes the importance of considering not only the usability aspects but also the emotional dimensions, including thoughts, feelings, and behaviors that products or services evoke in users. Such measurements as we have been able to appreciate

throughout this chapter, can be approached through the measurement of electronic signals from the brain and peripheral components in response to the emotional state of the user.

Among the technologies that various authors have integrated and explored to understand and interpret the physiological and electrophysiological responses of the user in the vehicle, we can find the following list as being some of the more common ones:

- Electroencephalogram (EEG) is used to measure the electrical activity of the brain. By placing an array of electrodes on a person's scalp, EEG captures variations in the voltage potential as a result of the activation of groups of neurons in the brain [26, 27].
- Eye tracking [28] is a technique used to track the movement of the user's eyes. By capturing and analyzing this data, researchers can gain valuable insights into what users are specifically looking at and the sequence in which their eyes move across different points of interest. Thanks to the evolution of computer vision technologies, most eye tracking technologies use high-speed vision systems to track the movements. However, there are also some eye tracking systems that work by electromyography, measuring the activation of the muscles around the eyes.
- Galvanic Skin Response (GSR), also known as Electrodermal Activity (EDA) or Skin Conductance (SC), is a physiological measurement that detects variations in the conductivity of the skin as a result of the activation of the sweat glands on the extremities of the subject. These variations can be linked to changes in the user's arousal, engagement, and potentially stress [29].
- Heart Rate Variability (HRV) HRV sensors analyze the beat-to-beat variations in the time intervals within a given period of sinus rhythm. The variations in the rhythm can be associated with stress and physical activity [30].

It should be noted that even though each technology provides valuable data, the level of complexity and interaction required during a driving scenario usually requires the integration and combination of various technologies synchronized to complement and provide the necessary data for a full assessment of the driver's state and interaction. It should also be mentioned that, even though it is not further developed in this section, the vehicle complexity has led to the need for developing and analyzing the impact of the various visual and physical interfaces in vehicle scenarios; some examples can be found in [31, 32]

From the examples mentioned in this section, we can appreciate some of the multiple environments and areas of opportunity that the integration and communication between the user and their environment present, while also addressing a bit of what has been explored and which technologies are required.

2.3 Educational context

In recent years, the term “Education 4.0” has been approached with high relevance by different authors who have conceptualized it according to the well-known periods of the four industrial revolutions. Therefore, it has been analyzed

how the evolution of technologies has influenced the education sector for a long time. Hence, pedagogy, teaching philosophies, educational models, information sources, learning methods, and the roles of students and teachers have been considered as part of the given concepts. Furthermore, it is observed that in this period, methodologies, practices, and activities seek to make the processes of knowledge generation and information transfer more personalized, efficient, accessible, and flexible. In this section, we will learn a bit about the evolution of education into the Education 4.0 field, and we will explore how it can be enriched by the integration of BCI technologies. Education 4.0 is understood to be composed of four key components: (i) incorporation of new pedagogical processes and practices, (ii) implementation of current and emerging Information and Communication Technologies (ICTs), (iii) use of innovative facilities to improve learning processes, and (iv) training and development of desirable competencies in today's students.

The technological evolution and the corresponding revolutions that have been witnessed throughout the evolution of humanity have proved, so far, to be a process with accelerated growth. Each new revolution, as will be analyzed further on in this section, has led to the necessity of developing and adapting educational strategies. One of the main issues in the development of engineering and technology education is the search for a sound conceptual basis for the curriculum, which gains more relevance as the nature of technology education has changed due to a faster-paced evolution [33]. This change has transformed the educational focus from emphasizing skills to emphasizing competencies and technological literacy. Just like in the case of the industrial revolutions, the transformation in education has traditionally been slow [34]. However, time is no longer a luxury that higher education institutions have, as they need to adapt to prepare students to adjust, solve problems, and overcome challenges yet to come [35].

While earlier technologies such as the telegraph, the steam engine, and the electric motor illustrate a pattern of complementary innovations that eventually lead to dramatic productivity improvements [36] by contributing to the muscle power of industries, digital technologies are performing a similar task but with brainpower, allowing us to overcome many limitations rapidly and open up new frontiers with unprecedented speed [37, 38]. One way we can view the new structure and focus of universities is through the appearance of the “entrepreneurial university,” whose interaction with industry and government has been described by previous authors as the triple-helix model [39]. The interaction between industry and universities has gained more attention as universities transcend from capacitation centers to centers capable of collaborating in the creation of spin-offs [40]. In this context, the quality of education strategies and the quality of educators impact engagement with industry [41] and, consequently, directly impact the employability of students.

To fully grasp the evolutionary potential and implications of Education 4.0 and its relationship with technological revolutions, we need to understand the implications of the phases that led from original higher education, going through its beginnings, to Education 1.0, 2.0, and 3.0 [42], to finally delve deeper into Education 4.0 and its relationship with Industry 4.0 [43].

As expressed by Miranda et al., the advancement in educational needs and challenges has led to the creation and proposal of new educational methodologies, but also to the need and development of new technologies that

may improve such educational impact [44]. With this focus, as expressed by Miranda et. al., the advancement on educational needs and challenges has led to the creation and proposal of new educational methodologies, but also to the need and development of new technologies that may improve such educational impact [44]. With this focus, BCI has allowed us to approach the challenge of optimizing the education process from two main fronts. One of them is the use of neuro feedback, as presented by [45]. The implementation of BCIs, as explained by Folgieri, can impact the memory, creativity, and concentration of students [46]. This technology has also shown some potential to train and rehabilitate students with neurodevelopmental disorders, as further explored by Papanastasiou et al. [47].

2.4 Art and entertainment

The development and understanding of the relationship between the user and their mental state has opened the door to the exploration of the relationship between the emotional state of the user and the actions they perform. In this manner, one of the areas to explore is the area related to the expression of the user through alternative methods such as art. With this in mind, BCIs allow the exploration and development of interfaces that enable therapists and researchers to better grasp the correlation between therapeutic care and emotion. As explained by Scott, the BCI can provide users with the ability to communicate or help therapists understand the patient's emotional state [48]. One such example of these implementations is the one presented by Tang et al., who present a BCI implementation for the development of paintings through brain control [49]. The connection between the emotional state of the user, analyzed via the BCI, has led to the concept of affective BCI (aBCI), as mentioned by Mühl et al., who explore the affective response of a subject to auditory, visual, and tactile stimuli, which activate different areas of the brain [50].

Just as the understanding and analysis of the brain via the BCI, both as a tool for measurement and as a control tool, allow us to further expand our knowledge of the workings of the brain, there is one additional door that opens: the connection of multiple brains through BCIs. Such an idea is explored and proposed in a video game scenario by the team of Bonnet [51]. These possibilities arouse the curiosity of the video game industry, where users are constantly demanding new ways to interact and collaborate with each other, sometimes motivated or inspired by science fiction and, at other times, inspired by the evidence of existing gaming BCI technologies, such as those summarized by Nijholt [52].

3. Study cases

In this section, we will present three study cases where we will explore some of the more concrete research lines that our research team pursues as a result of the exploration of the possibilities of user monitoring. The intention of these cases is to summarize the key findings and potential that BCI integration has in areas of application such as elder care, home automation, and driver monitoring. Prior to the development of the cases, we present a summary of the cases.

The first case will present the importance of understanding the impact that the technologies in the vehicle have on the attention process of the users. In this way, the

case presents the development of a study where the use of brain interfaces (EEG) was employed to evaluate the impact that ADAS systems had on the concentration and response of the users. Following the case, we will further explore how those initial tests have led to the evolution of research at the Smart Electro Mobility Lab (LEMI in Spanish).

The second case presents an approach for the integration of user state analysis to improve the home automation system's response and adaptation for user comfort. In this case, we explore an AAL system referred to as emotional domotics, where we will present how the integration and analysis of the brain and physiological responses of users subjected to various stimuli in a test environment controlled through KNX technology have led to the principles and theories of monitoring technology evaluation for integration into living and work environments.

The third case is an evolution of the living environment, where the researchers seek to further improve the quality of life for elderly users, especially those afflicted with dementia. In this project, we will start by exploring how brain interfacing has allowed us to develop and propose various technologies with the objective of improving cognitive decline monitoring and identifying patterns of activities that may lead to unsafe environments for the users. This research line intends to fully understand the variations derived from a declining brain to build accessible solutions capable of maximizing the independence and comfort of those afflicted by these symptoms.

3.1 First case: BCI applied in driving environments

3.1.1 Rationale and scope

Brain–computer interfaces (BCIs) embedded in intelligent transportation systems (ITS) are transitioning from concept to practice. In road vehicles, passive BCIs use non-invasive EEG to estimate a driver's cognitive and affective state and then modulate driver assistance accordingly, rather than emitting one-size-fits-all alerts. Naturalistic on-road studies show that EEG can be recorded in traffic and used to evaluate whether risk-dependent alerts actually capture attention. Methods included synchronized road/driver cameras with EEG along a fixed route, revealing that identical alerts may help or hinder depending on the driver's evolving state[53]. These findings motivate human-in-the-loop, closed-loop assistance, where neural and behavioral state estimates determine when and how to intervene – a perspective formalized by the ADMAS [54]. In **Figure 2**, we can observe a graphical summary of the research line implementation described throughout the subsections of Section 3.1, First Case.

3.1.2 Neurosensing hardware for in-vehicle BCIS

EEG is the most practical neurosignal for driving BCIs, thanks to millisecond-level temporal resolution and well-studied correlations with vigilance, workload, and affect. Two electrode families are relevant:

- Wet electrodes: low contact impedance and cleaner traces, but they require gel, skin preparation, and a longer setup.

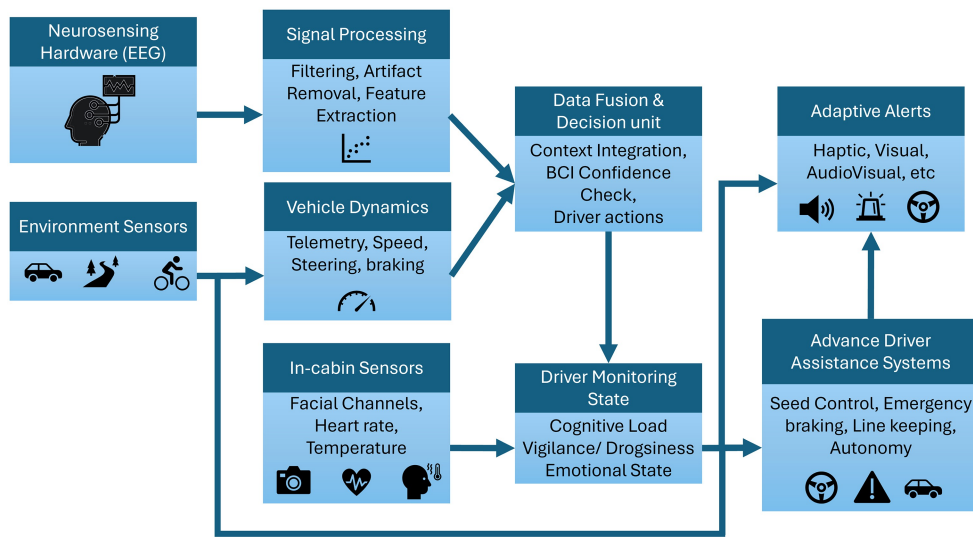


Figure 2.
ADMAS research: Graphical summary.

- Dry electrodes: quick, gel-free setup suited to real driving, at the cost of higher impedance and potential motion sensitivity, are still favored for in-car deployment [54].

Low-cost prototypes demonstrate that usable EEG can be acquired in vehicles. A six-channel, battery-powered Wi-Fi headset reports approximately 0.8% analog front-end nonlinearity, effective tens of nanovolt resolution via oversampling, and a 0.8–45 Hz bandwidth. These parameters align with affect and attention markers [55]. Such designs enable simulator cohorts and fleet pilots without clinical rigs.

Montages for driving emphasize frontal leads (executive control/valence), central (sensorimotor readiness), and parietal–occipital (vigilance/visual attention). Given motion and comfort constraints, headbands that trade spatial resolution for robustness are common; therefore, feature sets should prioritize broadband powers and asymmetries that remain stable under slight shifts in placement.

3.1.3 Experimental designs in driving bcis

1. Naturalistic on-road alerting. Drivers follow an urban route while risk-dependent visual or audio alerts are issued; synchronized road/cabin cameras, plus EEG, allow designers to quantify alert usefulness and timing in real traffic[53].
2. Emotion-aware assistance. In simulators and instrumented drives, planned maneuvers are paired with real-time affect inference (EEG baseline + optional facial channels). Results across ADMAS trials show passive alerts alone are not uniformly beneficial; assistance should be gated by the inferred state[54, 56].

3. Emotion-to-control concepts. Several systems use EEG-derived affect estimates on the valence–arousal plane to tune cabin settings (e.g., trigger music therapy, soften secondary stimuli), thereby closing the loop between neural state and assistance, and moving the HMI beyond simple alerting [57, 58].

3.1.4 Signal processing for robust on-road EEG

In-vehicle pipelines target motion/ocular artifact suppression while preserving low-frequency vigilance correlates. A typical chain includes band-pass filtering (~0.5–30 Hz or up to 45 Hz), notch removal, re-referencing, amplitude-based rejection, and independent component analysis (ICA) with component pruning for blinks and EMG [53]. Continuous signal-quality indices are recommended to down-weight noisy windows.

For robustness and interpretability, we prioritize log-band power features in the δ , θ , α , and β ranges at frontal/parietal locations, frontal α -asymmetry to index valence, Hjorth parameters for succinct temporal characterization, and higher-order crossings for noise-tolerant time-domain cues. With sufficient electrode coverage, functional connectivity measures can be added [59, 60, 61].

For assistance loops, actionable latencies <250 ms are realistic with filter-bank energies or short-time Fourier features, updating in sliding windows that avoid excessively heavy transforms, which increase delay [60, 61].

3.1.5 Learning paradigms and adaptation

- Classical pipelines: Using power spectral densities from low-density headsets, KNN/SVM/RF can classify discrete emotions or valence–arousal quadrants with high accuracy and fast enough for embedded deployment under controlled, platform-matched conditions [57, 59].
- Deep and graph models. 1D-CNNs, CNN-RNN hybrids, and graph neural networks capture richer spatiotemporal structure and have advanced the state of the art on public datasets; however, performance degrades with cross-driver/session shifts [60, 61].
- Domain adaptation for road-rage: Cross-subject generalization improves when respecting EEG topology and adapting node-wise with transferable attention; in simulated driving, this raised road-rage recognition to ~85.6%, a promising path to trigger de-escalation policies (e.g., soft alerts, calming HMI) [62].
- Model maintenance: Practical deployments use device-specific training, 1–3-minute onboarding calibration, drift detection, and few-shot updates after electrode repositioning. When classifier confidence drops, systems should fall back to sensor-only ADAS policies.

3.1.6 BCI outputs changing the assistance

BCIs add value when their outputs change behavior in measurable ways:

Alert gating and escalation. When β increases while occipital α coherence decreases, the driver is likely overloaded, which means that non-essential alerts

should be suppressed. If θ rises, signaling under-arousal, alerts should be escalated and delivered via multiple modalities. Field studies with on-road EEG have demonstrated that neural attention metrics can confirm alert perception and inform the retiming of later alerts [53].

Timing and spatialization. When an alert seems to be missed, the system advances the timing and increases the intensity of the next cue, while spatializing it toward the actual location of the hazard (for example, sounding from the right if the risk is on the right). This is consistent with the 360° alert concept [56].

HMI adaptation: When sustained high arousal/negative valence persists, reduce secondary tasks and visual clutter; optional “emotion-to-control” concepts (e.g., music therapy) can be engaged to restore calm[58].

Safety interlocks: When BCI confidence is low (e.g., poor signal quality or excessive artifacts), the system should automatically fall back to sensor-only ADAS behavior, so assistance degrades gracefully without relying on uncertain neural inputs [59, 63].

3.1.7 Human-centered and ethical considerations

Systems should minimize raw data exposure (on-device processing; export only low-dimensional state estimates), obtain explicit consent/opt-out, and maintain functionality parity for users who decline BCIs (camera/behavioral approximations). Brief, context-aware explanations (“Why this alert now?”) increase trust; equitable performance demands validation across age, culture, and neurodiversity, plus careful management of dry-electrode impedance differences [54, 56].

3.1.8 Limitations and near-term priorities

Motion artifacts, comfort, and calibration burden remain primary constraints. While ICA-based pipelines recover useful signals under road vibration [53], production systems must reduce setup time and maintain continuous data-quality checks. Near-term priorities include: (i) calibration-light classifiers with confidence-aware fallbacks; (ii) synchronized logging with vehicle kinematics for outcome-based evaluation; (iii) cross-subject/domain adaptation for robust affect detection [59, 61, 62]; and (iv) low-cost instrumentation of fleets and simulators to link road context with driver state at scale [63].

3.1.9 Current research focuses on BCI in driver monitoring

The topic of BCI applied to driving environments is gaining traction as global actors take part in a technological race to improve the driving experience, and vehicle capabilities evolve. The search for high comfort fuels research in a global view. As a demonstration of this trend and some of the key actors in this research line, we can observe the map in **Figure 3**. The map represents the scholarly output from 2020 to 2025 of the top 100 publishers. This result, obtained with the Elsevier SciVal tools [64], resulted from the following query: “Brain Computer Interface” AND (“Driver Attention” OR “Assistance Systems” OR “Driving”). As we can observe, the main actors in the field are China, the USA, and India; however, we can also observe a growing importance in Europe. The collection illustrated through this

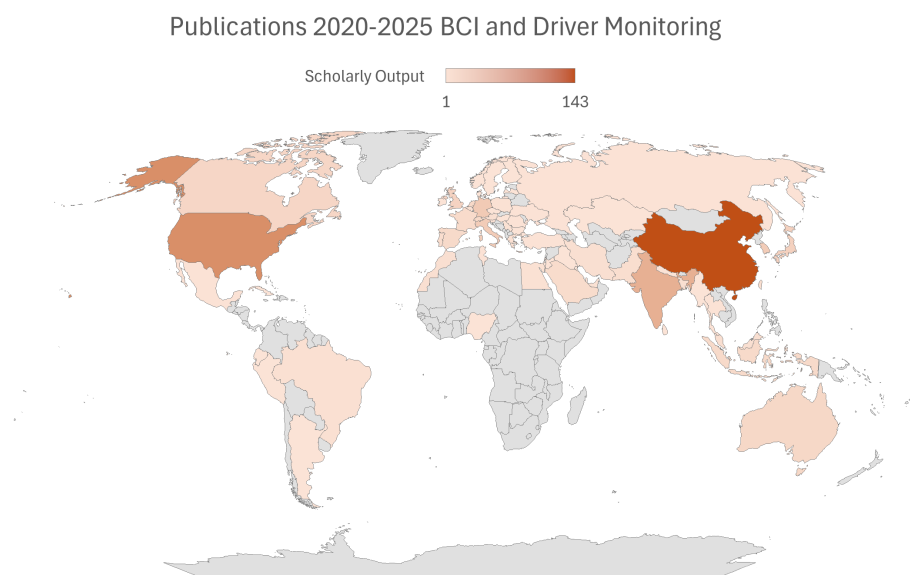


Figure 3.
 MAP of BCI and driver monitoring. © elsevier, “BCI_ADMAS,” scival, report generated on: October 2, 2025.

map includes a total of 475 publications indexed on Scopus. Even though most of the publications are centered on engineering and computational systems, the disciplines of sociology, psychology, and economics are starting to gain traction.

3.2 Second case: emotional domotics research track

Considering the previous introduction of the environment and user monitoring technologies, in this subsection, we will explore our first study case: the Emotional Domotics (ED) research line.

In the initial stage, the ED research line was driven by the recognition that stress and other negative psychological conditions are increasingly present in modern life and affect well-being. The main objective was to design and build an active space that reacts to the emotional state of its inhabitants through real-time modulation of environmental variables such as light, temperature, and relative humidity [65]. To accomplish this, a review of home automation technologies was conducted, which led to the selection of the KNX communication standard because of its flexibility, compatibility, and capacity for integration with custom monitoring solutions, including BCI technologies [66].

For the detection of emotions, the first experiments relied on computer vision methods, particularly the Facial Action Coding System (FACS) [67], as implemented in the iMotions software with the FACET (Emotient) module, which achieved an accuracy of 97% [68], together with standardized emotional stimuli from the International Affective Picture System (IAPS). Participants carried out short tasks in controlled environments where lighting and other ambient factors could be manipulated, and their emotional responses were analyzed to assess how environmental variables influenced users' emotions. Results confirmed that emotional variations could indeed be induced and measured in this way, which

validated the concept of building a testing booth for dynamic environmental modulation.

From conceptual validation, the research moved to the actual design and construction of a controlled testing booth capable of dynamically regulating environmental variables such as temperature, lighting intensity and hue, relative humidity, and CO₂ concentration. The testing booth integrated KNX-based sensors and actuators, configured through ETS5 software, and relied on iMotions for emotion recognition through the analysis of facial expressions, as well as galvanic skin response and heart rate measured through a Shimmer wristband [69]. All these data streams were merged in MATLAB/Simulink for mathematical modeling [70], which enabled correlations between environmental changes and emotional responses to be established [66].

From a BCI perspective, the testing booth represents a foundational framework where neural interfaces could be naturally integrated. Instead of relying solely on facial or peripheral physiological signals, BCIs could provide direct neural markers of stress, attention, or cognitive load during experimental tasks. For instance, a BCI could detect shifts in mental workload during the Stroop test or changes in relaxation levels during recovery phases, as seen in [69], offering a richer dataset. By feeding these neural signals into the same KNX-MATLAB coding, the system could adjust environmental conditions proactively based not just on external expressions but also on internal brain activity.

After analyzing the correlation between the impact of environmental conditions on users' emotional behavior, the research progressed toward the development of a comprehensive system and mathematical model capable of correlating environmental conditions with emotional states [71]. Using a response surface methodology (Box-Behnken design), the effects of temperature, light intensity, and color composition (percentages of red and blue light) were analyzed across 81 experimental runs. Participants were also exposed to standardized affective stimuli, while their emotions were captured primarily through facial expression recognition. The analysis prioritized micro-expressions and immediate peaks in emotional response, rather than long-term averages, to capture emotion variations.

The results produced preliminary mathematical models linking environmental factors to five main emotions (joy, anger, sadness, fear, and disgust) with moderate predictive power. The models revealed that environmental manipulations had a stronger effect on emotional dynamics than standardized visual stimuli, showing that smart environments can directly modulate emotional states. The study concluded that adaptive, emotion-based control systems for inhabitable spaces are feasible and could significantly improve quality of life, productivity, and stress management.

Finally, the ED research line advanced toward creating a flexible communication framework capable of supporting not only home automation but also systematic UX evaluation. Using the KNX standard as the backbone, a scalable infrastructure was developed that integrates sensors, actuators, and control modules to dynamically regulate environmental conditions such as temperature, humidity, lighting, and air quality [72]. This setup was conceived as an interactive space in which user responses could be correlated with specific environmental manipulations.

The framework demonstrated its potential in a case study involving the evaluation of detergent bottle designs. Within the testing booth, participants were exposed to different lighting conditions while interacting with detergent bottle prototypes, and their emotional responses were tracked. This allowed us to identify

which design features evoked positive or negative reactions, showing how the environmental modulation with affective monitoring provided a robust tool for UX research, design validation, and the creation of more responsive interactive spaces.

From the perspective of BCIs, this framework represents a natural entry point for UX evaluations based on neuroactivity. BCIs could extend the system by supplying real-time neural indicators of attention, engagement, workload, or affective valence, offering data streams that are both immediate and deeply tied to users' cognitive and emotional states. In the bottle case study, for instance, BCI measurements could detect subconscious preference signals or frustration markers that facial expressions alone might miss. This would enable the capture of not only observable emotional reactions, but also the implicit neural correlations of UX.

Integrating BCIs into the KNX-based communication system would close the loop between brain, body, and environment. Environmental variables could be adjusted dynamically, not only in response to observable emotional cues but also in anticipation of user needs revealed by neural activity. This could transform the testing booth into a neuro-UX lab, capable of guiding product design, architecture, marketing, education, or workstations based on direct brain-environment interaction. Thus, BCIs would elevate ED from an emotion-driven automation system to a cognition-aware adaptive framework for understanding and shaping UX. The general structure of the Emotional Domotics Research line presented in this section is summarized by the flow diagram in **Figure 4**. In this diagram, we can observe how, even though the initial research line focused on the experience of the

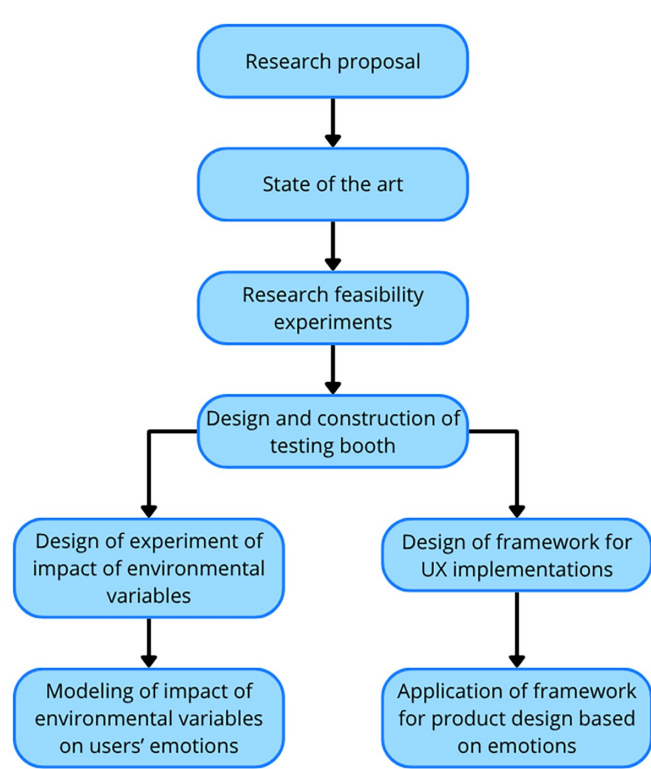


Figure 4.
Emotional domotics research line structure.

Publications 2020-2025 BCI and Emotional Domotics

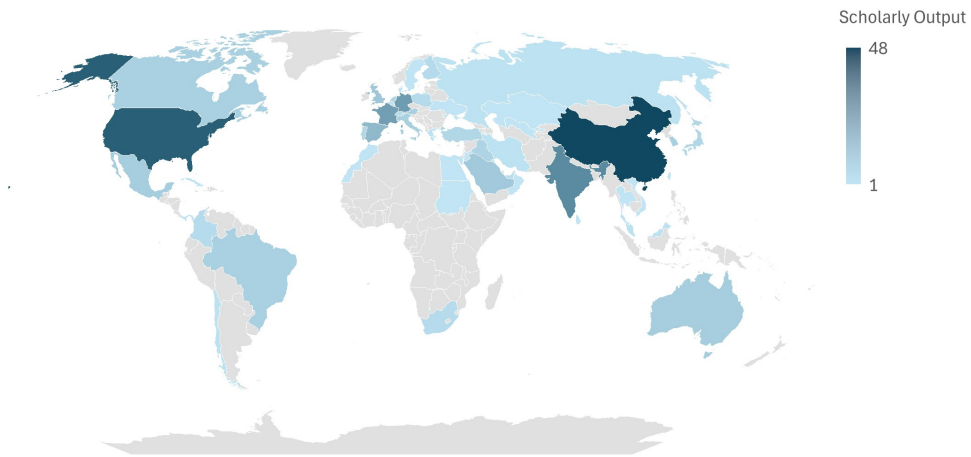


Figure 5.
MAP of BCI and driver monitoring. © elsevier, “BCI_AAL,” scival, report generated on: October 2, 2025.

inhabitant due to environmental variables, this line soon evolved and branched out into other UX analysis implementations. These evolution paths led to the implementation in elder care that will be presented in the third case.

3.2.1 Current research focuses on BCI in emotional domotics

The topic of BCI applied to smart environments, referred to in this document as Emotional Domotics, has gained traction thanks to trends such as population aging, the evolution of IoT, and recent progress in smart systems capabilities aided by Big Data. As a demonstration of this trend and some of the key actors in this research line, we can observe the map in **Figure 5**. The map represents the scholarly output from 2020 to 2025 of the top 100 publishers. This result, obtained with the Elsevier SciVal tools [73], resulted from the following query: “Brain Computer Interface” AND (“User Monitoring” OR “User Experience” OR “UX” OR “Smart Home Systems” OR “Ambient Assisted Living”). As we can observe, the main actors in the field are China, the USA, India, and central Europe. The collection illustrated through this map includes a total of 242 publications indexed on Scopus. Even though most of the publications are centered on engineering and computational systems, medicine and nursing are gaining traction. This last point is briefly explored in the following section.

3.3 Third case: diagnosis and treatment approaches for neurodegenerative diseases in aging

This section will examine the use of BCI in the development of research on aging and its evolution toward applications in one of the most common conditions associated with aging: dementia.

As people age, some diseases become more frequent, and dementia is most prevalent among individuals over 65 years of age [74]. Dementia refers to a set of symptoms that may arise from different diseases, the most common being

Alzheimer's disease. These symptoms include the gradual decline of cognitive functions such as memory, language, orientation, and attention [75].

Dementia, in its early stages, is difficult to diagnose. For this reason, one of our main objectives has been the application of technologies to support specialists in the diagnosis of mild cognitive impairment through the use of biomarkers that enable early detection and provide objective and measurable data. As a first approach, we explored the monitoring of participants while performing standard cognitive screening tests, measuring both their emotional responses and physiological signals, such as heart rate and galvanic skin response [76].

By linking emotional states with performance in each section of the cognitive test, it was possible to identify which parts of the test might represent greater difficulty for the participant. This approach also strengthens diagnosis and helps to address well-known challenges, such as test repetition and educational background. As a next step, we have worked on the integration of EEG into already automated screening tests to analyze brain wave activity in real time. Devices such as the EMOTIV EPOC X have been used to extract features, including engagement, attention, stress, interest, and band power in specific frequency bands [77].

Since some types of dementia, including the most common one, Alzheimer's disease, are irreversible to date, many efforts have also been directed toward non-pharmacological treatments that focus on the rehabilitation of cognitive functions. In this context, the use of EEG in rehabilitation therapies has been widely applied to monitor changes in brain waves associated with the progression of symptoms and with the aim of maintaining cognitive functions [78]. This approach has not only been used with individuals living with dementia but also as a strategy to strengthen cognitive abilities and act as a protective factor against the risk of dementia in the aging population [79].

The integration of BCI devices as a complementary tool in the diagnosis of cognitive impairment represents a promising opportunity to strengthen existing screening tests and monitor brain activity in relation to the progression of these conditions. This integration, combined with monitoring during cognitive rehabilitation, offers the possibility of linking changes in brain activity with specific therapeutic exercises that may prove more effective for patients.

3.3.1 Current research focuses on BCI in cognitive systems

The topic of BCI applied to cognitive systems, with a focus on dementia and cognitive decline, has been impacted by population aging throughout the globe. As a demonstration of this trend and some of the key actors in this research line, we can observe the map in **Figure 6**. The map represents the scholarly output from 2020 to 2025 of the top 100 publishers. This result, obtained with the Elsevier SciVal tools [80], resulted from the following query: "Brain Computer Interface" AND ("Dementia" OR "Diagnosis" OR "Cognitive Rehabilitation"). As we can observe, the main actors in the field are China, India, and the USA. However, we can also appreciate a slight interest throughout Europe and Latin America. The collection illustrated through this map includes a total of 530 publications indexed on Scopus. Most of the publications on this topic, as expected, referred to computational systems; however, we can also appreciate a high contribution in the fusion between medicine, pharmacology, psychology,

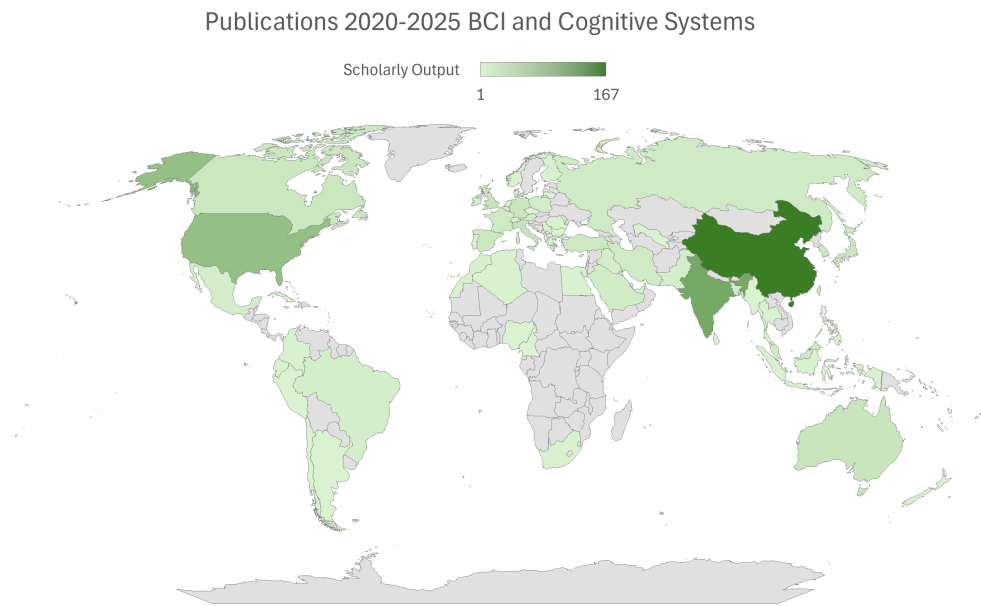


Figure 6.

MAP of BCI and driver monitoring. © elsevier, “BCI_cognitivesystems,” scival, report generated on: October 2, 2025.

and sociology. This confirms the importance of the transdisciplinary progress that this area has toward future evolution.

4. Conclusions

In this document, we were first introduced to some of the areas and technologies that have impacted or been impacted by the advancements in BCI technologies. We were presented with some of the implementations linked to user communication, interaction, and experience to contextualize the potential presented by such advancements. Later, we were presented with three research lines as cases, where we explored some of the results that the implementation of monitoring systems has nurtured. These cases are intended to demonstrate how, even though the initial focus may be smart homes, driving, or elder care, each line ended up gravitating toward the integration of BCIs. This integration reflects the potential that development and research present by pursuing the link between the user’s brain and their various technologies. This interconnection could eventually lead to the integration of the user into the IoT and CPS systems.

In the case of elder care, it is imperative to improve monitoring and communication technologies, as current demographic trends are leading to the aging of the population, which in turn will increase the cost and complexity of caring for an elderly population, with the corresponding afflictions but with a reduced workforce.

In the case of home automation, we can see that the integration of the user as part of the system in smart buildings and smart cities will improve the quality of life and can, in turn, improve the efficiency of the resources being consumed. Resource consumption optimization through improved control systems that guarantee the comfort of the users through monitoring and communication will allow for a

reduction in the impact of the carbon footprint and, in turn, contribute to achieving the sustainable development goals proposed by the United Nations.

Finally, in the case of vehicles, with an increasing demand and advancement into AV, the pursuit of interconnectivity between the vehicles and the drivers will help to improve the safety of the driver and the pedestrian. It is becoming increasingly urgent to improve the safety of vehicles, as even the most advanced AV system requires the user to be responsive and pay attention to the roadway in case of emergencies; however, this ability can be affected by external factors. Thus, the integration of the BCI will allow the vehicle to optimize its interaction with the driver and be capable of applying emergency measures in case of need.

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Conflict of interest

The authors declare no conflict of interest.

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Perspective Chapter: Brain-Computer Interfaces in the Context of Military Medical Training – Potential, Limitations and Ethical Perspectives

Hristina Georgieva and Ivan Popivanov

Abstract

In the last two decades, the development of neurotechnology, and in particular Brain-Computer Interfaces (BCI), has made rapid progress, changing not only the face of medicine and neuroscience, but also security and defense strategies. The military industry has become one of the leading drivers of innovation in this field, investing significant resources in the integration of BCIs to enhance the cognitive abilities, resilience, and effectiveness of military personnel soldiers. This transformation has led to the emergence of new concepts such as cognitive warfare, the neuro-enhanced soldier, and militarized rehabilitation. Since their inception, the military industry has been at the forefront of many innovations in this area, with investments primarily aimed at improving the capacity of military personnel. As a result, the concepts of the “enhanced soldier” and militarized rehabilitation have also emerged. The present study examines precisely this intersection between technology, training, and ethics. Particular attention is paid to the role of BCIs in the training and development of military medical personnel – a field in which the boundary between treatment and control, between assistance and manipulation, is particularly fragile. There are fragmentary and insufficient publications and facts on the topic. The aim of the work is not simply to track technological progress, but to raise questions about the moral, legal, and social consequences of the implementation of neurotechnologies in a military context. In a world where the brain is increasingly viewed as a battlefield, the responsibility of science is not only to create but also to make sense of its boundaries.

Keywords: human-computer interaction, brain-computer interfaces, military medical training, medical ethics, neurolaw, cognitive training, bioethics

1. Introduction

“The future must be one in which military doctors never doubt that they are, first and foremost, doctors bound by universal medical ethics.”

George Annas

Imagine a military medical team moving through a collapsed city district after an airstrike. The night is illuminated by the cold light of headlights mounted on drones that hover silently above the ground, and above them, in the dark sky, moves an autonomous evacuation vehicle – pilotless but with precise control, ready to pick up wounded or endangered civilians. At the head of the column is a military medic wearing a high-tech helmet with a brain-computer interface built into it. He does not hold a joystick in his hands and does not utter commands but simply thinks – and the technology executes. “Pulse... identify wounded...” The triage robot (an autonomous ground module equipped with sensors and a portable hemostasis system) reacts instantly and takes the set course, while the data on the wounded’s vital signs appear in its operating system. This scene no longer belongs to science fiction.

Systems for mind control of drones and ground platforms have been experimentally demonstrated by American and Australian researchers – operators were able to direct robotic dogs and aircraft using brain signals with up to 94% accuracy [1].

Similarly, clinical studies on paralyzed patients have shown that brain-computer interfaces can control robotic limbs, restoring movement through electrical stimulation of the spinal cord [2].

Scientists at the University of California, San Francisco, have helped a paralyzed man control a robotic arm with just his thoughts. The brain-computer interface (BCI) translates brain signals into movements using artificial intelligence that can adapt to changes in brain activity. Unlike previous systems that have operated for 24–48 hours, this device has been operating stably for seven months without needing to be readjusted. After training with a virtual arm, the participant began to control a real robotic arm, being able to move objects, open a cupboard, and even pour water. “Collaboration between humans and artificial intelligence is the next phase in the development of these technologies,” says Professor Karunesh Ganguly, who led the study, which was published in *Cell*. The team is now refining the system to make the movements smoother and more natural – a step that could restore independence to people who have lost their motor skills [3].

Military medicine logically integrates this technology into evacuation and triage training, where every second counts. Using neuro feedback and adaptive artificial intelligence, the medic trainee learns to maintain cognitive resilience under stress, and the system adjusts the noise filter in the brain data.

The main achievements in the field include advances in robotics, biometric diagnostics, and unmanned systems. Robotic and remote surgery are now becoming a reality on the battlefield.

Biomedical sensors can transmit physiological data to military personnel in real-time, which improves the situational awareness of teams on the ground.

Today, minimally invasive and precise procedures can now be performed (even remotely) thanks to small robots. A good example of complex, delicate, and invasive surgical interventions is the Da Vinci Xiu system. It was developed in the 1980s for the purposes of the US Army, the goal being to provide the ability to perform surgical operations in military field conditions. The Da Vinci Xi robot expands the

surgeon's capabilities through a 3D view of the surgical field and allows for more precise movements and better results in complex interventions. Of course, very soon after its creation, this system has also found application in civilian medicine, the result being a shorter hospital stay, less blood loss, faster recovery, and a return to normal life. Several Da Vinci robots are already operating in Bulgaria, one of which is at the Military Medical Academy (MMA).

Unmanned systems are mainly used in logistics and reconnaissance in hard-to-reach areas. Medical drones deliver emergency medicines and medical equipment to military units.

In this chapter, we explore brain-computer interfaces in the context of military medical education. We present their potential, limitations, and ethical challenges in different ways. Different interfaces and their potential applications in education and medicine are matched with the emphasis on military medical education and training. In parallel, we also pay attention to international regulations.

Qualitative methods, such as document (content) analysis and observations, were used in the analysis of the available literature to outline the real potential and limitations of modern brain-computer interfaces in the context of military medical education. The analysis was based on current scientific sources, case studies, and pilot studies that show how technologies function outside the laboratory environment.

2. From theory to reality

In the twenty-first century, the world's leading powers are directing the development of combat technologies toward platforms that do not simply follow orders, but have a high degree of autonomy, adaptability, and reliability. These are not just machines but intelligent systems designed to navigate and operate in a dynamic, often unpredictable combat environment. It is precisely such characteristics that form the core of the concept of the so-called "war of the future" or "intelligent war." However, with the advent of these technologies, it turns out that the old control models – through manual commands, physical activity, or voice instructions – are no longer relevant. They limit the speed and effectiveness of the reaction, and in the conditions of high-risk missions, this can cost human lives. Therefore, attention is directed to a new type of communication between man and machine – direct, contactless, instantaneous. Here, brain-computer interfaces (BCIs) play a key role, allowing the operator to control robotic systems – including unmanned aerial vehicles – through their thoughts, without the need for traditional means of control [4].

Military conflicts place humans in extreme situations of uncertainty and resource scarcity, of direct or indirect threat, in which quick and correct decisions are of vital importance. Technologies that, until recently, sounded like science fiction, including BCI and artificial intelligence, are now actively entering the reality of the battlefield. They not only complement the skills of medical personnel but actually expand their capabilities to respond faster, more precisely, and more safely in critical situations. At the intersection of advanced training, neurotechnology, and automation, a new model of action on the battlefield is being sought.

Military medicine is a specialized branch of occupational medicine focused on the health needs and risks faced by military personnel. It encompasses the prevention

and treatment of diseases, injuries, and specific syndromes associated with military operations, as well as the effects of modern weapons, psychological stress, noise, and toxic substances [5]. The organization of medical support includes all levels – from first aid at the front to advanced hospitals – with the aim of rapid treatment and restoration of personnel's operational capability [6].

The primary mission of military medicine is to provide comprehensive medical support, improve the health of service members, and enhance the success of military operations. Military medical training integrates medical knowledge with military training, aiming to prepare specialists for a wide range of challenges, including:

- providing field medical care,
- conducting traumatological interventions,
- work in extreme conditions (combat operations and natural disasters)
- collaboration in multidisciplinary and international teams.

Modern technologies are transforming this process, providing new training tools see **Figure 1**, such as virtual training to simulate real-world combat and crisis situations, and telemedicine to maintain the operational readiness of teams. In peacekeeping operations involving the use of force, ensuring effective and continuous medical support in a risky environment is critical to the survival of casualties. This requires organizing medical evacuation outside the combat zone, including the establishment of casualty collection points, transport with medical and general military equipment, and aeromedical evacuation. Planning takes into account the commander's decisions on the conduct of the combat operation, the expected number of personnel casualties, potential civilian and prisoner casualties, and coordination with coalition partner medical structures for hospitalization and ongoing care [7].



Figure 1.
Combat training under smoke and low-light conditions. The image is from the archives of the Military Medical Academy, Sofia, Bulgaria: (by courtesy of the Military Medical Academy Sofia).



Figure 2.
Soldiers administer tactical field care during a training exercise. The image is from the archives of the Military Medical Academy, Sofia, Bulgaria: (by courtesy of the Military Medical Academy Sofia).

Medical support in such operations requires rapid and accurate assessment of the health needs of the victims, as well as taking measures for the necessary sanitary protection and prevention of epidemics. To be effective, the medical formation must be able to be quickly deployed to the disaster site, have mobile and portable medical equipment, as well as qualified specialists. It is especially important that the teams can communicate with the victims in their language, which facilitates care and increases the effectiveness of interventions [7]. Interaction in combat teams, discipline, and integration in the “man – team – combat equipment” systems are specific and require targeted research for optimal understanding and management (see **Figure 2**).

In peacekeeping operations, medical units often operate in diverse climatic and geographical conditions. The diversity of these regions creates a unique set of factors that must be considered when planning medical support. Therefore, the medico-geographical characteristics of the terrain are a key element in the successful organization of assistance [7]. Medical professionals often encounter unfamiliar injuries, new protocols, or unfamiliar equipment, especially when interacting in a multinational environment where the main reference point is the complaints and symptoms of the patients, rather than established diagnoses [7]. In this context, Brain-Computer Interfaces offer the opportunity to create an adaptive, personalized, and realistic training environment.

3. Man versus machine or together?

What is a brain-computer interface? Brain-computer interfaces (BCIs) represent one of the fastest-growing areas in modern neurotechnology. Originally developed for medical purposes – to assist or restore motor functions in patients with neuromuscular disorders – these systems are now seen as a key component in the future of human-machine interaction. BCI technologies work by capturing and

analyzing the electrical activity of the brain, translating neural information into digital commands used to control external devices. This allows the user to interact with computer systems, prostheses, or other technological platforms solely through mental activity, without the need for physical movement. Unlike traditional control methods that require motor activity, brain-computer interfaces directly extract the user's functional intent (the desire for action, movement, or communication) and convert it into an executable command.

The BCI system consists of three main components:

- A device for capturing brain activity – this can be a special hat, headband, or headphones equipped with sensors that detect the electrical signals sent by neurons in the brain.
- Computer processing and analysis – the received signals are transmitted to special software, which, using complex algorithms, calculates what exactly a person wants to do. It is like a translator between thought and machine language.
- A device or application that executes the command – this could be anything from turning on a light to controlling a computer program or a robot. Once the computer “understands” the intent, the device translates it into an actual action.

BCI systems provide feedback that informs the user about the success of the action and supports the learning and adaptation of brain activity, most often measured by electroencephalography (EEG). In this way, BCIs translate thought into actual action, expanding the possibilities for interaction for people with limited motor functions [8]. In her article “Brain-Computer Interfaces (BCIs), Explained,” Brooke Becher describes how BCIs allow users to control external devices through their brain activity by converting the electrical signals of neurons into digital commands. The technologies can be non-invasive (electrodes on the scalp), semi-invasive, or invasive (placed close to the brain tissue). Sensors capture brain activity, and software interprets intentions, allowing control of prosthetics, rehabilitation systems, and smart home technologies – literally turning thought into action [9].

All these discoveries reveal the potential of BCI – to translate thoughts into concrete action. This, in turn, expands the possibilities for people with physical disabilities and motor deficits [10]. Directly connecting brain activity to external devices through BCI can allow soldiers to interact with equipment or send signals even in situations where physical actions or speech are impossible or limited. In the context of combat medicine, this means not only faster diagnosis and timely response, but also the opportunity to save many lives.

As we see, the role of the Brain-Computer Interface (BCI) is becoming increasingly important and necessary, not only in civilian and military medicine but also in the training of military personnel and military doctors.

4. Neurointerfaces and the transformation of combat training

Military strategists such as Admiral S. O. Makarov understood the importance of psychological resilience and adaptation to extreme battlefield conditions as early as

the late 19th century. As he himself noted: “A person is created in such a way that he will go to a seeming death when the danger is familiar to him, but even the noise of the bilge water will frighten him if he is not used to it. Accustom people to this noise, and they will fight against breakthroughs to the last opportunity.” In this sense, General M. I. Dragomirov emphasized that “the situation during exercises and maneuvers should approach a battlefield,” insisting on integrated training and psychological preparation. These insights today find their technological analog in the application of brain-computer interfaces (BCI) in the context of military training. Neurostimulation, cognitive profiling, and virtual simulations can prepare cadets (see **Figure 3**) for the realities of war by modeling psychophysiological responses and thus improving their resilience even before their first real encounter in a combat environment [11].

Monitoring soldiers’ brain activity through integrative neuroplasticity systems (IONS) is used to assess soldiers’ emotional states, attention, and cognitive workload [12]. This optimization facilitates personalized training by overcoming the limitations of traditional communication. This, in turn (as demonstrated by DARPA’s Targeted Neuroplasticity Training (TNT) project), expands the “cognitive battlefield” through cognitive skill acquisition.

The Alert Warrior Enablement (AWARE) program demonstrates that safe brain stimulation can enhance the alertness and cognitive abilities of soldiers during combat, while integration with unmanned systems and AR devices allows for hands-free control of drones and robots. In the long term, BCIs can establish a human-computer network for conscious command control and intelligent autonomous interaction between soldiers, commanders, and combat systems [13].

In the field of military training, BCI allows the creation of adaptive simulations that take into account the brain activity of trainees, improving cognitive responses and reflexes (see **Figure 4**). Brain-Computer Interface technology offers wireless control of weapons and equipment through mental commands, reducing the need for physical participation and increasing effectiveness in dangerous conditions. In addition, BCIs offer a revolutionary approach to military medical training, allowing

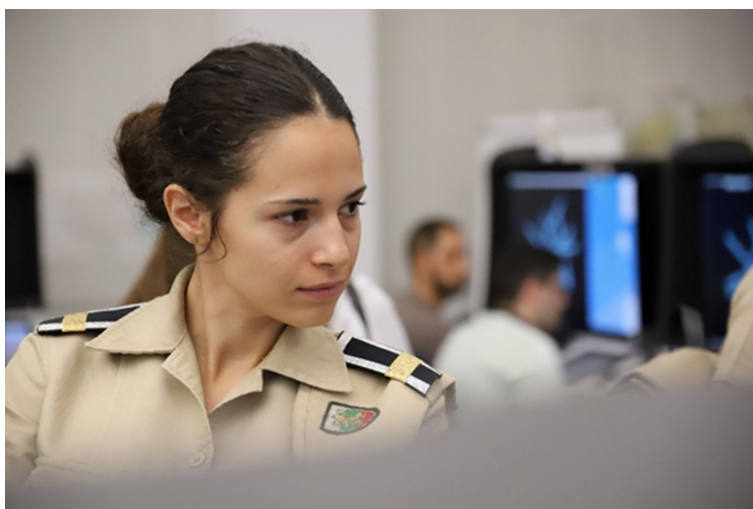


Figure 3.
Military medical doctor. The image is from the archives of the Military Medical Academy, Sofia, Bulgaria: (by courtesy of the Military Medical Academy Sofia).



Figure 4.

Soldier advancing in a smoke-filled training exercise. The image is from the archives of the Military Medical Academy, Sofia, Bulgaria: (by courtesy of the Military Medical Academy Sofia).

the “transmission” of collective expert memory directly to recruits. Skills that are usually learned after hundreds of operations or missions can be integrated into the mind of the trainee in weeks. The combination of neural recording, artificial intelligence, and virtual reality creates adaptive simulations that literally immerse trainees in realistic combat scenarios, without risk to their lives.

After World War II, especially at the end of the 20th and the beginning of the 21st centuries, the training of military doctors changed significantly. Training programs now include new areas such as tropical medicine, prevention of infectious and epidemic diseases, and emergency and trauma care. Specialized modules on dealing with chemical, biological, radiological, and nuclear risks are also included. These changes reflect global health challenges, the dynamics of modern conflicts, advances in technology, and new types of weapons that medical professionals encounter daily on the battlefield [14, 15].

Improving cognitive skills (reducing errors, improving attention and decision-making in dynamic conditions, etc.) is just one of the applications of BCI in training cadets. BCI-controlled simulators allow for the mastery of complex surgical techniques, enabling medical specialists to respond in real time to combat injuries and to control autonomous medical devices with their thoughts. This not only improves teamwork but also builds the psychological resilience of military doctors in conflict zones.

At the same time, the deployment of BCIs in conflict zones raises various ethical and legal issues, some of which are: the protection of personal data, informed consent and voluntary participation, and, of course, the potential misuse of the technology and dependence on the interface.

5. Before we press the button

In his book *The Age of Artificial Intelligence and Our Human Future*, Henry Kissinger expresses concern about decision-making based on algorithms. He argues

that this may undermine human intuition and experience as sources of understanding and processing knowledge [16]. The main threat, he argues, is not the potential for digital slavery or dependency that technology could create, but rather the gradual weakening of the connection between knowledge, knowledge, and experience.

He warns that thinking can be replaced by pure information processing and that our world can become vulnerable to erroneous commands. The abilities of artificial intelligence – to learn, perceive, evolve, and surprise – have the potential to transform human identity and the sense of reality in ways that have remained unknown since the beginning of modernity [16].

In his study “Words against Neutrons,” Professor Stoyan Stavrou [17] emphasizes the critical role of language and communication in recognizing and managing dangers that remain invisible to human senses. He argues that new technologies – including micro – and nanomaterial solutions – can cause harm that occurs gradually and remains imperceptible until the moment when their impact is already irreversible. According to the author, the main mechanism for prevention and early response is not visual control, but the ability of people to “listen” and interpret risks through words, concepts, and discursive practices. Words perform a dual function: they inform about the invisible and, at the same time, create a rhetorical framework that allows awareness, discussion, and formulation of ethical and normative behavior before the occurrence of real harm. In this context, literature, science, and law are connected in a single mechanism for preventive risk management. Art. Stavrou emphasizes that the failure or lack of verbal interpretation of invisible dangers can have catastrophic consequences for humanity, highlighting the example of Chernobyl and the importance of seeking truth through discourse. The discussion of invisible harms and their recognition through words provides a conceptual framework for managing risks, even when direct intervention is difficult or impossible [17].

According to Stoyan Stavrou, effective management of the risks thus present requires argumentative and ethical “deliberation” with clear safety standards and rules, as well as protocols for informed consent and monitoring of results. According to him, words and communication itself in training are the main mechanisms for the prevention and responsible use of brain-computer interfaces (BCIs), ensuring that the technological potential itself is realized without compromising human rights and health.

In the spirit of the broader ethics of responsibility, philosopher Hans Jonas reinterprets Kant’s categorical imperative, viewing it through the prism of concern for the future: “Act in such a way that the consequences of your actions are compatible with the preservation of real, human life.” Kant’s imperative takes on particular significance in the context of brain-computer interfaces (BCIs), which are changing not only the way we interact with machines but also our understanding of autonomy, will, and responsibility. When a machine begins to obey thought, the line between intention and action itself narrows considerably. This creates both unprecedented opportunities – especially in the fields of medicine and defense – and significant risks: misinterpretation of intention, blurring and dissipating personal responsibility in decision-making, and the potential use of technology in ways that damage “the future possibilities of this life.” In this sense, Jonas’s principle reminds us that the more we act through technologies like BCIs, the more urgent the need to think not only about efficiency but also about the ethical limits of what we can and

should do. On the other hand, Jonas emphasizes that only humans can be responsible, thanks to their consciousness and their ability to make moral decisions [18].

The closer the connection between human consciousness and machines.

The closer the connection between human consciousness and machines, the greater the responsibility that must be assumed by those who make decisions about their development, regulation, and control.

Jonas emphasizes the need for knowledge that does not simply explain the present but also anticipates possible future scenarios. Therefore, he introduces the concept of “comparative futurology” – hypothetical knowledge about the future, in which priority is given to negative forecasts rather than utopian hopes. It is precisely the fear of possible disintegration – not paralyzing but constructive – that drives responsible action. This “right fear,” according to Jonas, is an indispensable part of moral decision-making, especially when it comes to technologies that touch the very essence of man [18]. In the case of BCI, this means not only developing and implementing highly effective systems but also creating mechanisms for ethical control, transparency, and political accountability. Jonas does not deny that such an approach will limit some of the scientific and technological freedom – but it is precisely in this limitation that the maturity of a responsible society is manifested, which thinks not only about the possible but also about the permissible [18].

The modern revolution in warfare is moving toward smaller, mobile, and remotely controlled forces, but its effectiveness depends on reliable communications, sensors, and protection against cyberattacks – vulnerabilities that limit the idea of “pure” virtual warfare. Brain-computer interfaces (BCIs) accelerate this transition by enabling direct, hands-free control of drones, robots, and medical systems, but at the same time, the integration of BCIs increases the risk of satellite and communication channel dependency, the possibility of mind-control manipulation, and, last but not least, ethical and legal consequences. This, in turn, requires human oversight and new legal frameworks – a hybrid technology-intensive transformation, but with a strong emphasis on communications resilience, cyber-protection, and moral control when using BCIs [19].

In his book *Between Two Ages: America’s Role in the Technotronic Era* [20], Zbigniew Brzezinski writes: the accelerated replacement of manual labor by machine labor increases the need for continuous training and the rational use of skills, while universities are expected to become think tanks for sustainable policy planning and social innovation. He warns that the technotronic revolution, aided by audiovisual communications, fragments perceptions of reality and exacerbates global inequalities, questioning the sustainability of human values [20].

Contemporary thinkers such as Harari, Fukuyama, and Habermas also express similar concerns, emphasizing transhumanist perspectives: the integration of man with high technology risks changing the fundamental physical and cognitive characteristics of man to such an extent that it calls into question his freedom, identity, and autonomy.

These observations emphasize that the future of humanity is closely linked to the opportunities and risks of technological impact, which are also directly relevant to the topic of brain-computer interfaces and their potential in transforming cognitive abilities and learning [18].

The French philosopher Luc Ferry notes that the development of new technologies requires regulation that is neutral in form but deeply political and

ethical in nature, to prevent the so-called Promethean arrogance – the human tendency to exceed the limits of measure with our own creations. This warning finds direct reflection in the field of brain-computer interfaces (BCIs), especially when used in military training, where the ability to learn, respond, and control through thought requires a new type of responsibility. Instead of regulation, however, we observe accelerated technological progress, accompanied by legislative lag [18].

6. Ethics: The line between “can” and “should”

One of the main problems facing the construction of a universal international ethic is the lack of a common ideology, religion, or political system that would unite humanity around shared moral guidelines.

All this makes it really difficult and almost impossible to create universally valid ethical principles that are valid for all cultural, temporal, and political contexts. And in a field such as military medical training, an environment in which a person is subjected to strong emotional, physical, and moral pressure, the problem is even more delicate. History has proven, so far, that even ordinary people, placed in extraordinary situations, can perform actions that they themselves would consider immoral. The social or technological impact of the situation can provoke our moral reflexes and rearrange the norms of what is acceptable and what is not.

The introduction of brain-computer interfaces (BCIs) in military medical training puts the issue of ethics in a completely new perspective. On the one hand, as we pointed out above, BCIs offer modern opportunities for accelerated learning, integration of cognitive data in real time, and effective simulation of combat conditions. On the other hand, the technological context can change the very way medical staff perceive such a situation, the pain, and even the patient – especially in the context of interaction with an interface.

In the actions of drone operators carried out through screens, buttons, and commands, which Professor Stavrou discusses in detail, namely: the operator using a BCI risks losing the direct empathic connection with the person [21]. The interface is not just a mechanism – it systematizes perception and creates a moral distance between the “operator” and the “victim.” Therefore, the integration of BCI into military medical training should not be seen only as a technological innovation and tool, but also as an ethical task, requiring careful analysis and new frameworks for responsibility. In the context of modern high-tech conflicts, the concept of interface warfare, which includes remote control of combat systems and drones, guarantees a fundamental change in the traditional understanding of military responsibility and risk. According to the analysis of Professor Stoyan Stavrou in “Challenge the Law!” [22], the removal of the physical immediacy of the battlefield leads to the dehumanization of the participants: the operator of the remote device becomes the administrator of a machine, and the goal takes the form of an abstract point or target. This virtualization of the military act reveals new ethical and legal challenges, as the traditional criteria for justice in war – physical presence, immediate risk to the lives of combatants, and mutual participation in the conflict – are eliminated. Stavrou emphasizes that such technologies transform war into a systemic operation between things and data, in which old military values, such as courage and endurance, give way to priorities for operator precision and efficiency. From the point of view of military ethics, this requires a reassessment, above all, of the concept of

responsibility and justice: remote warfare creates situations in which actions are carried out with minimal personal risk but with potentially severe consequences for civilians or unprepared participants, and this, in turn, requires new regulatory frameworks and evaluative standards [21].

Psychological experiments conducted by American psychologists Philip Zimbardo and Stanley Milgram demonstrate how human behavior can be shaped by power and environment. People are more likely to submit to systems that provide resources, structure, and ideology – even when this leads to actions that contradict their personal morals. Roles, uniforms, and distance are factors that can nullify a sense of empathy and responsibility [23]. And this is extremely important in the context of military medical training, especially with the introduction of high-tech weapons systems and brain-computer interfaces (BCI).

When training is conducted through virtual reality, simulations, and direct control through thought, there is an immediate risk that personal ethics will be displaced by functionality and efficiency. The more abstract the actions, the easier it is to lose the human dimension, such as suffering, responsibility, and care. Therefore, the integration of BCI should not only focus on their technical capabilities but also on the creation of such learning environments that support moral judgment, human empathy, and conscious responsibility.

In the course of our research, we conducted an interview with Assoc. Prof. Dimitar Prodanov, a physician and computer scientist, and researcher at IMEC and IICT-BAS, who shared his important observations on the present and future of brain-computer interfaces (BCIs). Regarding data confidentiality, Assoc. Prof. Prodanov emphasized that it can only be guaranteed “by adhering to a strict regulatory regime.” This approach is also essential for ensuring the security and integrity of brain data collected through brain induction devices (BCIs). For the future of technology, he expects “rapid development of non-invasive BCI and the establishment of non-medical applications.”

This prediction reflects the trends toward a wider penetration of the technology in various fields, outside of strictly medical frameworks. Regarding the reliability of BCI in a stressful military environment, Assoc. Prof. Prodanov stated that he is not familiar with military applications and that “civilian applications are not designed to work in extreme conditions.” This clearly shows that the adaptation of these technologies to combat environments is still a challenge that requires further research. Finally, on the issue of the risk of mind manipulation through BCI, he warns: “Yes – there is such a danger as the technology advances. Nita Farahani writes a lot about the risks to personal autonomy.” This aspect requires serious attention, especially in the context of ethical norms and the protection of human rights.

The closer MCIs get to consciousness, the more acute the questions of cognitive autonomy and the right to mental integrity arise. The principle of autonomy requires free and informed consent, but military discipline questions the complete freedom of choice in the use of MCIs. The principle of beneficence emphasizes the benefits of cognitive enhancement, but it carries the risk of losing human empathy when machine efficiency prevails. The principle of non-maleficence warns of possible cognitive overload and neurological risks associated with neurostimulation and virtual training. The principle of justice emphasizes unequal access to technology and the danger of misuse of brain data, leading to new forms of “neuro-equality.” (see **Table 1.**)

Principle	Traditional medicine	Military medicine with BCI	Ethical risks
Autonomy	Free informed consent	Limited by military hierarchy and pressure	Freedom of choice threatened
Charity	Health care	Rehabilitation, but also “strengthening” for combat	Instrumentalization of man
Non-injury	Avoiding harm	Medical/psychiatric side effects, cyber risks	Potential for control and manipulation
Justice	Equal access to care	Limited access, military privilege	Social and global inequality

Table 1.
The table lists some of the risks characteristic of the specific field of activity.

7. Summary and outlook

Military objectives may conflict with medical and ethical standards, and the social implications of neurotechnology may raise unforeseen moral and legal conflicts. The main challenges to implementing MCI in military medical training include protecting the mental autonomy of service members, ensuring informed consent, and preventing the manipulation and misuse of personal data. High-tech integration also carries the risk of psychological and operational dependency, which can reduce critical thinking and the autonomy of personnel. The solution requires a strict ethical framework, which is clearly stated in the UNESCO (United Nations Educational, Scientific and Cultural Organization) Draft Recommendation on the Ethics of Neurotechnology [24].

In the context of military medical training through brain-computer interfaces (BCIs), five key “neuro-rights” should be considered, which shape the ethical framework for the use of these technologies:

- Right to mental privacy – protection of brain data from unauthorized access, which is especially critical for sensitive information generated during training and task performance.
- Right to personal identity – ensuring that neurointerventions do not violate or alter the essence of the learner’s personality.
- Right to free will – protection against unwanted influence or manipulation of decisions through the use of neurotechnologies in the educational process.
- The right to equal access to neurotechnology (fair access) – preventing social and economic inequalities that may arise from the limited distribution of these technologies across various military units.
- Right to protection from bias – ensuring that brain data does not lead to new forms of stigmatization, profiling, or inequality in personnel assessment and selection.

Brain-computer interfaces (BCIs) have the potential to save lives, but this is only possible if their implementation ensures the preservation of individual autonomy,

dignity, and human rights. To achieve this, strategic collaboration between medical professionals, engineers, lawyers, military personnel, and ethicists is required, as well as international dialog to develop unified standards.

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Conflict of Interest

The authors declare no conflict of interest.

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Addressing the complexity of systems that cut across neural technologies, health sciences, artificial intelligence, education, mobility, and other domains requires multidisciplinary convergence. It is crucial to understand how these different elements interact, particularly when human behavior is involved. Recent technological advances in materials and sensors have made it relatively straightforward to access tools and devices that capture and measure brain activity in real time via neural signals. When these signals are properly processed, they can yield highly valuable information for a wide range of applications. The central purpose of the book *Brain-Computer Interface – Bridging Technology, Education, and Ethics* is to serve as a reference work that combines rigorous, formal theoretical foundations with a practical, application-oriented perspective. It features case studies, demonstrators, simulators, datasets, and experiments that illustrate the vast potential of BCI technologies and other techniques grounded in cognitive science and neuroscience. With this aim, we convened leading experts from around the world to contribute their diverse perspectives on the complex ethical and responsibility-related issues that emerge when these technologies are deployed in various fields. The central aim of this book is to illuminate the methods used to examine and characterize human behavior and its interaction with digital technologies. The viewpoints collected here encompass health, rehabilitation, and education, particularly STEM education, as well as disruptive and understudied topics in the BCI literature, such as democratic governance, neuro-rights, and cognitive dignity. Collectively, these chapters constitute an essential resource for researchers, educators, students, and policymakers who want to understand the extraordinary potential of BCIs to save lives, protect individual autonomy, and improve the human condition.

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