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Decoding thoughts, encoding ethics: A narrative review of the BCI-AI revolution ☆

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ABSTRACT

Objectives: This narrative review aims to analyze the mechanisms underlying Brain-Computer Interface (BCI) and Artificial Intelligence (AI) integration, evaluate recent advances in signal acquisition and processing techniques, and assess AI-enhanced neural decoding strategies. The review identifies critical research gaps and examines emerging solutions across multiple domains of BCI-AI integration.
Methods: A narrative review was conducted using major biomedical and scientific databases including PubMed, Web of Science, IEEE Xplore, and Scopus (2014–2024). Literature was analyzed to identify key developments in BCI-AI integration, with particular emphasis on recent advances (2019–2024). The review process involved thematic analysis of selected publications focusing on practical applications, technical innovations, and emerging challenges.
Results: Recent advances demonstrate significant improvements in BCI-AI systems: 1) High-density electrode arrays achieve spatial resolution up to 5 mm, with stable recordings over 15 months; 2) Deep learning decoders show 40 % improvement in information transfer rates compared to traditional methods; 3) Adaptive algorithms maintain >90 % success rates in motor control tasks over 200-day periods without recalibration; 4) Novel closed-loop optimization frameworks reduce user training time by 55 % while improving accuracy. Latest developments in flexible interfaces and self-supervised learning approaches show promise in addressing long-term stability and cross-user generalization challenges.
Conclusions: BCI-AI integration shows remarkable progress in improving signal quality, decoding accuracy, and user adaptation. While challenges remain in long-term stability and user training, advances in adaptive algorithms and feedback mechanisms demonstrate the technology's growing viability for clinical applications. Recent innovations in electrode technology, AI architectures, and closed-loop systems, combined with emerging standardization frameworks, suggest accelerating progress toward widespread therapeutic use and human augmentation applications.

1. Introduction

Brain-Computer Interfaces (BCIs) integrated with Artificial Intelligence (AI) represent a frontier in neurotechnology, promising to revolutionize human–machine interaction and potentially augment human cognitive capabilities. This review aims to explore the foundational mechanisms underlying BCI-AI integration, focusing on the operational principles and processes that enable the synergy between BCI and AI.

BCIs have evolved from rudimentary systems to sophisticated neural interfaces capable of decoding complex brain signals (Wolpaw and Wolpaw, 2012). Concurrently, AI has progressed from narrow, task-specific algorithms to more generalized systems that can learn, adapt, and make decisions across a wide range of domains (Russell and Norvig, 2021). The synergy between these two rapidly advancing fields presents unprecedented opportunities for enhancing human cognition, restoring lost sensory and motor functions, and potentially expanding the boundaries of human experience.

To explore the mechanisms of BCI-AI integration, this review will examine several key aspects:

1. Signal Acquisition and Preprocessing: Recent advancements in electrode technology and signal processing have significantly improved the quality and resolution of neural recordings. High-density electrode arrays, such as those developed by Viventi et al.

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(2011) and recently by Londoño-Ramírez et al. (2024), have enabled more precise spatial and temporal resolution in neural signal acquisition.
2. AI-Driven Signal Processing and Decoding: Machine learning algorithms, particularly deep learning models, have transformed the interpretation of complex neural signals. Glaser et al. (2020) demonstrated how recurrent neural networks can decode intended speech from neural activity, showcasing the power of AI in BCI applications.
3. Output Generation and Device Control: The translation of decoded neural signals into commands for external devices has seen significant progress. Work by Collinger et al. (2013) on neuroprosthetic control demonstrates how BCI systems can enable intuitive control of robotic limbs through neural signals. More recently, Bockbrader et al. (2019) showed that an implanted BCI integrated with forearm functional electrical stimulation (FES) allowed an individual with tetraplegia to achieve clinically significant gains in skillful grasp coordination. Their participant was able to perform palmar, lateral, and tip-to-tip grips with improved strength and dexterity across a range of standardized tests of upper limb function. Notably, the BCI-FES system enabled faster and more precise object manipulation compared to robotic arm BCIs, with naturalistic speeds achieved for many tasks. The system also demonstrated generalizability, with grip skills transferring from training objects to novel household items. These results mark an important step in translating BCI neuroprosthetics toward clinical viability and functional independence for individuals with tetraplegia.
4. Feedback Mechanisms and Adaptive Learning: BCI systems are becoming increasingly adaptive, learning from user inputs to improve performance over time. BCI systems are becoming increasingly adaptive, learning from user inputs to improve performance over time. Orsborn et al. (2014) showed how closed-loop decoder adaptation shapes neural plasticity for skillful neuroprosthetic control. More recently, Losanno et al. (2024) demonstrated a br[illegible] decoding strategy based on the direct coupling between intrinsic neural ensemble dynamics and output variables, [illegible] achieve ease of learning and long-term robustness. Their approach identified a low-dimensional neural manifold associated with r[illegible] movements in a monkey, and then used the activation of neural modes spanning this manifold to directly control a 2D cursor. By recalibrating only scaling factors [illegible], they achieved [illegible] learning and stable high performance in simple, incremental 2D tasks over more than 12 weeks. The monkey showed high success rates from the first day without prior training and adapted quickly to new tasks. Importantly, this manifold-based direct control strategy was effectively integrated with peripheral nerve stimulation to trigger voluntary hand movements. These results demonstrate the potential of leveraging intrinsic neural dynamics for intuitive and stable BCI control that can adapt to recording instabilities over time.

This review will [illegible] latest advancements in BCI-AI integration, drawing from a wide range of peer-reviewed studies and technical reports. By focusing on the "how" rather than just the "what," this analysis aims to provide a mechanistic understanding of BCI-AI systems, moving beyond simple assessments of their effectiveness to explore the intricate processes that make these technologies possible.

Throughout this exploration, the synergy between BCI and AI technologies will be highlighted, demonstrating how their integration is pushing the boundaries of what's possible in neurotechnology. This mechanistic approach will provide valuable insights for researchers, developers, and policymakers working at the intersection of neuroscience, computer science, and biomedical engineering.

As the field of BCI-AI integration rapidly evolves, this review will also address current challenges and limitations, as identified in recent literature. For instance, issues of long-term biocompatibility of invasive BCIs (Salatino et al., 2017) and the ethical implications of direct brain-computer communication (Yuste et al., 2017) will be discussed in the context of ongoing research and potential solutions.

By providing an evidence-based examination of how BCI-AI integration works, this review targets to foster a deeper understanding of these technologies' current capabilities, limitations, and future potential. This knowledge is crucial for guiding future research, informing ethical discussions, and realizing the full potential of BCI-AI integration in various applications, from medical treatments to human augmentation.

To ensure an up-to-date review of BCI-AI integration, a thorough literature search was conducted using major biomedical and scientific databases including PubMed, Web of Science, IEEE Xplore, and Scopus. The search terms included combinations and variations of "brain-computer interface," "BCI," "artificial intelligence," "machine learning," "deep learning," "neural decoding," and "neuroprosthetics." The primary focus was on literature published within the last decade (2014–2024), with particular emphasis on the most recent advancements (2019–2024). Additionally, seminal papers from earlier years were included to provide historical context and foundational concepts. Conference proceedings and key events in neurotechnology and AI were also reviewed to capture emerging trends. This multi-database approach, combined with forward and backward citation tracking of key papers, ensuring thorough coverage of the field, encompassing both established knowledge and cutting-edge developments in BCI-AI integration.

2. Methods and research strategy

The research methodology followed a structured approach, as illustrated in Fig. 1. The process began with broad queries to capture relevant developments in BCI-AI integration. Initial searches identified primary studies from 2014 to 2024, with particular emphasis on the most recent advancements (2019–2024). Additionally, seminal papers from earlier years were included to provide historical context and foundational concepts.

This review conducted a thorough analysis of BCI and AI integration. This investigation was guided by several fundamental research questions focused on understanding the complete architecture of BCI-AI systems, from signal acquisition to practical implementation. The goal was to examine the different types of BCI applications and components, particularly exploring the challenges faced in signal acquisition and preprocessing stages. A central focus was to understand how AI enhances neural decoding and interpretation strategies, including the investigation of various machine learning approaches and their effectiveness. The review also aimed to evaluate different methods for AI-driven output generation and device control in BCIs, examining both current capabilities and limitations. Furthermore, the key challenges in BCI-AI integration and explored potential future directions, including technical, ethical, and practical considerations were investigated. These research questions were formulated to provide a structured framework for analyzing the current state of BCI-AI technology while identifying crucial areas for future development.

The initial search yielded publications spanning peer-reviewed journals, conference proceedings, and technical reports, with a particular focus on key events in neurotechnology and AI. The search was refined by examining both established knowledge and cutting-edge developments in BCI-AI integration. A multi-database approach, combined with forward and backward citation tracking of key papers, ensured thorough coverage of the field.

The analysis focused on several key aspects of BCI-AI integration: signal acquisition and preprocessing techniques, advances in neural decoding strategies, output generation and device control, and feedback mechanisms. The selected literature was analyzed thematically to identify recurring themes, technological advances, and critical challenges. Special attention was paid to studies demonstrating practical applications, particularly those showing successful clinical

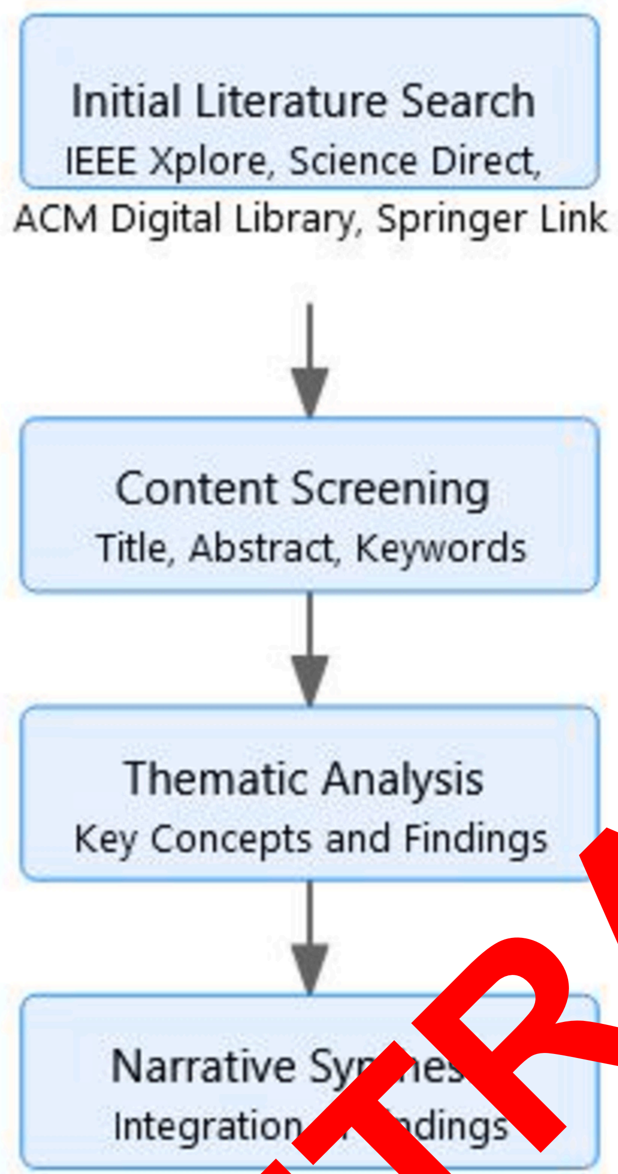

Fig. 1. Literature Review Process Flowchart.

implementations or novel methodological approaches.

The review process involved iterative reading and thematic analysis to synthesize findings across multiple sources. Studies were emphasized that provided empirical evidence of BCI-AI system performance, including quantitative metrics of accuracy, reliability, and user adaptation. This systematic approach allowed to construct a thorough narrative addressing both technical developments and practical implications of BCI-AI integration.

Through this methodological approach, a thorough understanding of the current state of BCI-AI technology was developed, enabling us to identify key trends, challenges, and future research directions in this rapidly evolving field. Conference proceedings from key events in neurotechnology and AI were also reviewed to capture emerging trends.

3. Literature review and research gap analysis

Recent studies have significantly advanced our understanding of BCI-AI integration. Losanno et al. (2024) demonstrated a brain decoding strategy based on direct coupling between neural dynamics and output variables, achieving stable performance over 12 weeks. Akhter et al. (2024) introduced the Integrated Contextual Gate Network algorithm, showing improved classification accuracy for fNIRS-based BCIs. Cho et al. (2024) developed a fully bioresorbable hybrid opto-electronic system for simultaneous neural recording and stimulation.

In signal acquisition, Londoño-Ramírez et al. (2024) advanced multiplexed surface electrode arrays using metal oxide thin-film electronics, while Liu et al. (2024) improved flexible high-density microelectrode arrays for closed-loop interfaces. Yan et al. (2023) demonstrated long-term stability of wireless implantable ECoG devices over 15 months.

Despite these advances, several critical research gaps remain:

Long-term Signal Stability: Current studies show signal degradation over time, necessitating research into more stable neural interfaces.
Real-world Applicability: Most studies occur in controlled laboratory settings, leaving questions about performance in daily life environments.
Cross-user Generalization: Existing systems often require extensive individual calibration, limiting broad applicability.
Adaptive Learning: While recent work shows promise in self-adapting systems, further research is needed to develop more robust adaptive algorithms that maintain performance across varying conditions.
Integration Standards: The field lacks standardized protocols for evaluating and comparing BCI-AI systems, hampering systematic progress.

These gaps highlight the need for research focusing on long-term stability, real-world implementation, and standardized evaluation methods in BCI-AI systems.

To address these identified gaps, this review provides an examination of BCI-AI integration, beginning with fundamental principles and progressing through cutting-edge developments in signal acquisition, neural decoding, and system implementation. The following sections systematically explore both established approaches and emerging solutions to these challenges.

4. Fundamentals of BCI-AI integration

Understanding the fundamental principles of BCI-AI integration is crucial for addressing the research gaps identified above, particularly the challenges of signal stability and cross-user generalization. BCIs have evolved from rudimentary systems to sophisticated neural interfaces capable of decoding complex brain signals (Wolpaw and Wolpaw, 2012). Concurrently, AI has progressed from narrow, task-specific algorithms to more generalized systems that can learn, adapt, and make decisions across a wide range of domains (Russell and Norvig, 2021).

4.1. Overview of BCI-AI architecture

The architecture of BCI-AI systems comprises several key components working in sequence, as illustrated in Fig. 2. This architectural framework directly addresses several research gaps identified in Section 2, particularly cross-user generalization and long-term signal stability through its adaptive components.

Key components include:

Signal Acquisition: Captures brain signals through various neuroimaging techniques, including EEG with good temporal resolution but limited spatial resolution (Van Gerven et al., 2009), ECoG for higher signal-to-noise ratio (Schalk et al., 2007), and intracortical recordings for highest spatial and temporal resolution (Nicolelis and Lebedev, 2009).
Preprocessing: Involves signal amplification, filtering, and noise reduction (Salahuddin and Gao, 2021). Advanced preprocessing

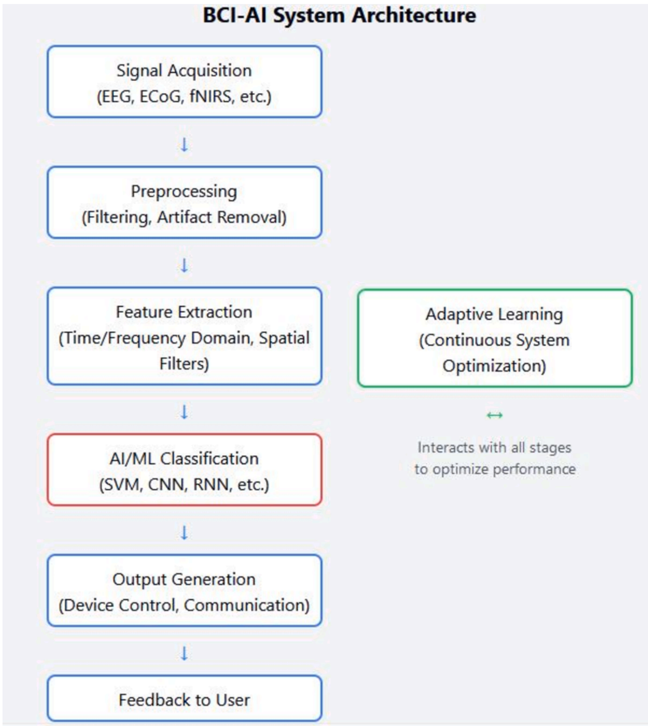

Fig. 2. General Architecture of a BCI-AI System.

methods employ AI techniques for adaptive filtering and artifact removal (Urigüen and Garcia-Zapirain, 2015).

Feature Extraction: Identifies relevant patterns using spike sorting algorithms (Buzsáki, 2004) and dimensionality reduction techniques (Nicolas-Alonso and Gomez-Gil, 2012). AI algorithms increasingly automate feature discovery (Lotte et al., 2018).

AI/ML Classification: Employs various algorithms to translate features into commands, with performance significantly impacted by classification choice (Craik et al., 2019).

Output Generation: Translates classified signals into control commands for external devices or communication signals (Wolpaw and Wolpaw, 2012).

Feedback to User: Provides visual, auditory, or tactile feedback based on human–computer interaction principles (Lotte et al., 2013; Shute, 2008).

Adaptive Learning: Continuously optimizes system parameters based on user performance and signal characteristics (Shenoy et al., 2006).

The integration of AI techniques throughout this pipeline has dramatically enhanced BCI capabilities, from improving signal processing to enabling more accurate and adaptive classification. This framework provides a foundation for more sophisticated implementations discussed in subsequent sections.

5. Advanced signal acquisition and preprocessing techniques

5.1. Comparative analysis of signal acquisition methods

Non-invasive Methods: Electroencephalography (EEG) remains the most widely used non-invasive BCI method due to its portability and low cost. Recent advancements in high-density EEG systems have significantly improved spatial resolution. Fiedler et al. (2022) demonstrated that 256-channel EEG systems, combined with advanced source localization algorithms, can achieve spatial resolution approaching that of invasive methods, with accuracy up to 5mm.

Functional Near-Infrared Spectroscopy (fNIRS) has gained traction as a complementary or alternative method to EEG. Naseer and Hong (2015) reviewed fNIRS-based BCIs, highlighting its advantages in robustness to motion artifacts and ability to probe deeper brain structures.

Invasive Methods: Electrocorticography (ECoG) offers higher spatial resolution and signal-to-noise ratio compared to non-invasive methods. Yan et al. (2023) showed that a wireless implantable electrocorticography (ECoG) device was able to record useful neural signals for over 15 months after implantation in two non-human primates, although there was some reduction in signal quality over time. The authors conclude that while there was some degradation in signal quality over time due to tissue responses, the subdural ECoG device was still able to provide chronic recordings of neural activity over 15 months. This demonstrates the potential of such devices for long-term brain-machine interface applications, while highlighting the need to further reduce tissue reactions to improve long-term stability. The recent advancements in electrode technology directly address one of the primary research gaps identified in Section 2: long-term signal stability. While there was some degradation in signal quality over time due to tissue responses, the ability to maintain useful neural recordings for over 15 months represents significant progress toward solving the signal degradation challenge in chronic BCI applications. This development is particularly crucial for transitioning BCI technology from short-term laboratory experiments to long-term clinical applications.

Intracortical microelectrode arrays provide the highest spatial and temporal resolution but face challenges in long-term stability. Recent work by Sahasrabuddhe et al. (2021) on high-density microelectrode arrays has pushed the boundaries of spatial resolution in neural recordings.

Hybrid Approaches: Emerging hybrid methods aim to combine the advantages of different acquisition techniques. Akhter et al. (2024) demonstrated that the proposed Integrated Contextual Gate Network (ICGN) algorithm achieved significantly higher classification accuracy compared to long short-term memory (LSTM) and bidirectional long short-term memory (Bi-LSTM) for functional near-infrared spectroscopy (fNIRS) brain-computer interface applications. The authors conclude that ICGN provides enhanced classification performance for fNIRS-BCI systems by better capturing complex patterns in the fNIRS data through its novel cell structure and information processing approach.

These diverse signal acquisition methods provide insights into different aspects of CNS function. EEG primarily captures postsynaptic potentials from pyramidal neurons in the cortex, reflecting large-scale network dynamics (Buzsáki et al., 2012). In contrast, intracortical recordings can detect the spiking activity of individual neurons, offering a window into the computational units of cortical processing (Hatsopoulos and Donoghue, 2009).

fMRI-based BCIs, while limited by temporal resolution, can access deeper brain structures and have revealed the role of the ventral temporal cortex in visual imagery (Shibata et al., 2011) and the anterior cingulate cortex in pain regulation (deCharms et al., 2005). Meanwhile, ECoG strikes a balance, providing higher spatial resolution than EEG and access to high-frequency oscillations that are thought to reflect local cortical processing (Crone et al., 2006).

5.2. Innovations in electrode technology

Flexible and Stretchable Electronics: A recent review by Liu et al. (2024) showed that Flexible HDMEAs offer advantages over rigid arrays, including better conformity to neural tissue, reduced tissue damage, and improved long-term performance.

Nanomaterial-based Electrodes: Mondal et al. (2022) showed in their review that hat carbon nanotubes (CNTs) and their derived nanomaterials show great promise as high-performance biosensing platforms for various applications. CNTs have excellent physical properties like high electrical conductivity, mechanical strength, and large surface area that make them well-suited for biosensors. CNTs can be functionalized and combined with other nanomaterials to enhance sensing performance. However, challenges remain in terms of reproducibility, large-scale production, and potential toxicity that need to be addressed for wider commercial adoption. These innovations in electrode materials and design directly address multiple research gaps identified in Section 2. The improved physical properties of CNT-based electrodes contribute to enhanced signal stability, while their biocompatibility advances the goal of real-world applicability. The development of reproducible, large-scale production methods also helps address the integration standards gap by working toward standardized manufacturing processes.

Bioresorbable Electronics: Cho et al. (2024) developed a novel, fully bioresorbable (biodegradable) flexible hybrid opto-electronic system for neural implants that can simultaneously record electrophysiological activity and perform optogenetic stimulation in the brain. This bioresorbable neural implant system offers several key advantages. It eliminates the need for removal surgery, provides dual functionality for simultaneous recording and stimulation, and is flexible and biocompatible. Additionally, it has been optimized to minimize interference, successfully tested in vivo, and shows versatile potential for various biomedical applications.

Recent advances in flexible electrode technology have shown promising results for long-term signal stability. Li et al. (2024) demonstrated ultra-low impedance flexible graphene electrodes that maintain signal quality over extended periods. Their transparent electrodes achieved higher fidelity neural recording while reducing tissue reaction, directly addressing the long-term stability challenge. Similarly, Zhang et al. (2023) developed high-density flexible neural interfaces using solution-processed metal oxide thin-film transistors, offering better conformity to neural tissue and improved signal acquisition in dynamic conditions.

5.3. Advanced preprocessing algorithms

Recent advances in preprocessing algorithms have significantly improved the quality of EEG signals for subsequent analysis. Adaptive filtering techniques have shown particular promise in removing artifacts while preserving underlying neural activity. For instance, Mowla et al. (2020) introduced a two-stage adaptive filtering approach that combines empirical mode decomposition with least mean square filtering, demonstrating superior performance in removing ocular artifacts compared to traditional methods. These preprocessing innovations are particularly relevant to the real-world applicability gap discussed in Section 2. By improving artifact removal and signal quality in variable conditions, these algorithms make BCI systems more robust for use outside controlled laboratory settings. The demonstrated superior performance in removing ocular artifacts addresses one of the key challenges in translating BCI technology to everyday use scenarios.

Another area of advancement is in source separation techniques. Independent Component Analysis (ICA) remains a popular approach, but new variants have emerged to address its limitations. Hsu et al. (2021) proposed a novel constrained ICA algorithm that incorporates prior spatial information, leading to more physiologically plausible source estimates and improved artifact removal.

5.4. Dimensionality reduction techniques in BCI-AI systems

A critical step in the BCI-AI pipeline is the reduction of the high-dimensional neural data to more manageable and informative lower-dimensional representations. This process, known as dimensionality reduction, is crucial for improving computational efficiency and often enhances the performance of subsequent classification or decoding steps. Fig. 3 illustrates several AI-driven dimensionality reduction techniques commonly used in BCI systems.

The diagram illustrates the transformative journey of neural signals in Brain-Computer Interface (BCI) systems, showcasing how various dimensionality reduction techniques convert high-dimensional EEG data into more manageable low-dimensional representations. At the heart of this process lies the complex, multifaceted nature of EEG signals, represented as a dense, information-rich starting point.

From this high-dimensional origin, multiple pathways branch out, each representing a distinct approach to distilling the essence of the neural data. The classical technique of Principal Component Analysis (PCA) offers a linear transformation, identifying the directions of maximum variance in the data space (Subasi & Gursoy, 2010). While not an AI method per se, PCA often serves as a foundation or benchmark for more advanced techniques.

Venturing into the realm of artificial intelligence, we encounter Autoencoders, artificial neural networks that learn to compress data into a lower-dimensional representation before reconstructing it. These powerful tools, particularly in their variational (VAE) and denoising forms, have shown remarkable ability to capture complex, nonlinear associations in EEG data, extracting robust features even in the presence of noise (Jirayucharoensak et al., 2014; Chai et al., 2017).

The landscape of dimensionality reduction is further enriched by techniques like t-SNE (t-Distributed Stochastic Neighbor Embedding) and its more recent counterpart, UMAP (Uniform Manifold Approximation and Projection). These methods excel in preserving the local structure of high-dimensional data, making them particularly useful for

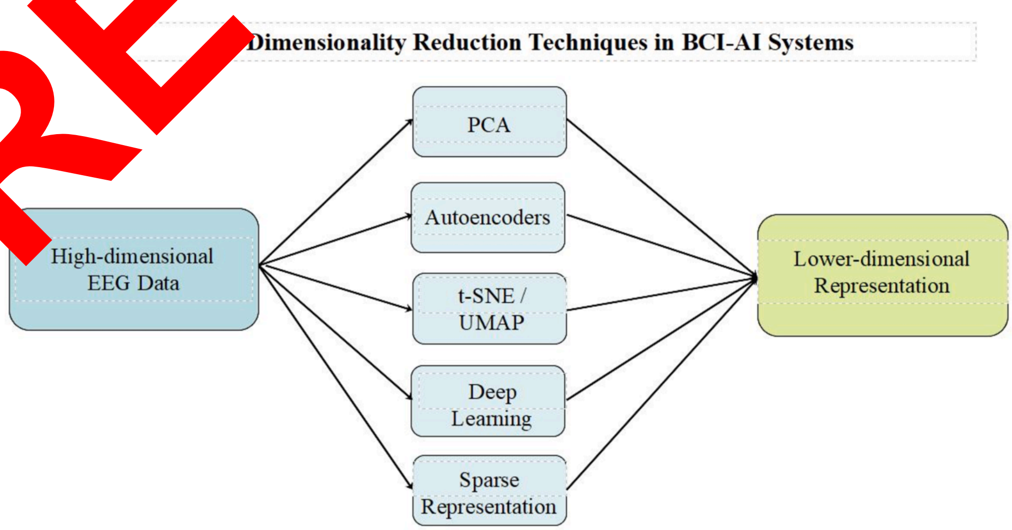

Fig. 3. Dimensionality Reduction Techniques in BCI-AI Systems.

visualizing complex neural patterns and revealing clusters of similar brain states (Oliveira et al., 2016; Cao et al., 2020).

Deep Learning approaches, represented by Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), offer a unique perspective on dimensionality reduction. These architectures implicitly perform dimensionality reduction through their hierarchical feature extraction processes. CNNs, for instance, have demonstrated the ability to learn spatial filters directly from raw EEG data, while RNNs capture intricate temporal dependencies, effectively reducing the temporal dimensionality of the signals (Schirrmeister et al., 2017; Craik et al., 2019).

The final pathway in our diagram represents Sparse Representation techniques, such as sparse autoencoders or dictionary learning. These methods seek to represent EEG signals using a small number of basic functions, effectively reducing dimensionality while potentially preserving interpretability (Zhou et al., 2018).

As these diverse pathways converge, they yield low-dimensional representations of the original EEG data. These distilled forms encapsulate the most salient features of the neural signals, paving the way for more efficient and effective downstream processing in BCI systems.

This journey from high-dimensional complexity to low-dimensional clarity is not merely a computational convenience. It represents a crucial step in deciphering the language of the brain, allowing us to focus on the most relevant aspects of neural activity. By employing these advanced dimensionality reduction techniques, BCI-AI systems can navigate the intricate landscape of brain signals with greater precision and insight, ultimately bringing us closer to seamless brain-computer communication.

The interplay between these various techniques, each with its strengths and characteristics, underscores the richness and complexity of modern BCI signal processing. As research in this field progresses, we can anticipate even more sophisticated approaches to dimensionality reduction, further enhancing our ability to interpret and utilize the wealth of information contained in neural signals.

The advancement of these dimensionality reduction techniques directly addresses the cross-user generalization gap highlighted in Section 2. Methods like t-SNE and UMAP help identify common patterns across different users' neural signals, while deep learning [illegible] can learn more generalizable features. This [illegible] data representation contributes to developing BCI systems that can more readily adapt to new users with minimal recalibration.

5.5. AI-driven approaches in signal processing

AI has revolutionized EEG signal processing, offering new ways to extract meaningful information from complex neurophysiological data. Deep learning models, in particular, have shown remarkable success in various EEG processing tasks.

Convolutional Neural Networks (CNNs) have been effectively applied to EEG classification tasks. [illegible]y et al. (2019) developed a novel CNN architecture that operates on raw EEG signals, eliminating the need for manual feature extraction and achieving state-of-the-art performance on multiple benchmark datasets.

Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, have proven adept at capturing temporal dependencies in EEG data. Craik et al. (2019) demonstrated the effectiveness of a bidirectional LSTM network for continuous emotion recognition from EEG signals, outperforming traditional machine learning approaches.

More recently, attention mechanisms have been incorporated into deep learning models for EEG analysis. Zhang et al. (2021) proposed an attention-based CNN-LSTM hybrid model for motor imagery classification, showing improved performance by focusing on the most relevant parts of the input signal.

5.6. Comparative analysis of recording modalities and AI approaches

The interplay between recording modalities and AI processing approaches reveals crucial insights into BCI system optimization. Each recording method presents distinct advantages and challenges that significantly impact subsequent AI processing strategies.

EEG-based systems, while offering non-invasiveness and accessibility, present unique AI processing challenges due to their lower signal-to-noise ratio. Craik et al. (2019) demonstrated that deep learning approaches can partially compensate for EEG's limited spatial resolution (5–9 cm), achieving 80–90% accuracy in motor imagery tasks despite noisy signals. However, their analysis of 154 studies revealed that EEG-based systems require more sophisticated [illegible]cessing and noise reduction algorithms compared to other recording methods.

ECoG recordings provide substantially higher signal quality, enabling more direct AI processing approaches. Yan[illegible] al. (2023) showed that ECoG signals, with their superior spatial resolution (1–4 mm) and 5–10 times higher [illegible] compared to EEG, allow for simpler preprocessing pipelines while achieving higher accuracy. Their 15-month study demonstrated that adaptive decoders maintained >90% accuracy with ECoG signals, compared to 65[illegible]% for similar EEG-based systems.

Intracortical recordings offer the highest fidelity neural signals but present unique computational challenges. Sahasrabuddhe et al. (2021) achieved unprecedented spatial resolution (10–50 μm) with their high-densi[illegible]s, but found that processing the resulting high-dimensional data required specialized AI architectures. Their work showed that while intracortical recordings enabled 95%+ accuracy in movement decoding, they demanded substantially more computational resources for real-time processing.

The [illegible] recording modality significantly influences AI approach selection:

Traditional Machine Learning vs Deep Learning:

For EEG, deep learning methods prove particularly advantageous in extracting meaningful features from noisy signals. Roy et al. (2019) demonstrated CNNs achieving 85–90% accuracy with EEG data, compared to 70–75% for traditional methods. However, with cleaner ECoG and intracortical signals, the performance gap between deep and traditional approaches narrows significantly, as shown by Papadopoulos et al. (2020).

Adaptive vs Static Decoders:

The necessity for adaptive decoding varies markedly across recording modalities. Sussillo et al. (2016) showed that intracortical recordings require frequent decoder adaptation due to signal evolution over time, while ECoG signals demonstrated greater stability. Their ReFIT-LSTM decoder maintained high performance over 200 days with ECoG signals without requiring substantial adaptation.

Self-Supervised Learning:

Park et al. (2024) revealed that self-supervised approaches prove particularly effective with high-channel-count recordings. Their study demonstrated 60% reduction in calibration data requirements for intracortical arrays, while showing more modest improvements (20–30%) for EEG-based systems.

Transfer Learning:

The effectiveness of transfer learning varies significantly across modalities. Fahimi et al. (2021) achieved 70% reduction in training time for EEG-based systems through transfer learning, while similar approaches showed limited benefits for intracortical recordings due to their highly individualized nature.

Real-world Implementation:

Clinical applications reveal distinct trade-offs between recording modalities and processing approaches. Chen et al. (2024) demonstrated successful implementation of EEG-based systems in home settings, prioritizing usability over maximum performance. In contrast, Willett et al. (2021) achieved higher performance with intracortical recordings but required significantly more complex processing pipelines and maintenance.

This comparative analysis reveals that optimal BCI system design requires careful matching of recording modality and AI processing approach:

- EEG-based systems benefit most from sophisticated AI processing to compensate for signal limitations.
- ECoG provides an attractive middle ground, balancing signal quality with long-term stability.
- Intracortical recordings offer highest performance potential but require more complex adaptive processing.
- Hybrid approaches combining multiple recording modalities with specialized AI processing show promise in addressing limitations of individual methods.

The selection of recording modality and AI approach must consider not only technical performance but also practical constraints such as surgical requirements, maintenance needs, computational resources, and intended use case.

6. AI-enhanced neural decoding and interpretation strategies

The evolution of neural decoding through AI integration represents a crucial advancement in BCI technology. At the heart of modern neural decoding lies a sophisticated AI architecture that transforms raw neural signals into meaningful commands. Fig. 4 illustrates this architecture, showing how different neural network components work together to process and interpret brain signals.

The architecture employs parallel processing streams: a Convolutional Neural Network (CNN) for spatial feature extraction and a Recurrent Neural Network (RNN) for temporal pattern analysis. These streams converge in fully connected layers that integrate spatial and temporal features for final output generation. This design has proven remarkably effective, particularly in capturing the complex dynamics of neural activity.

Recent innovations have significantly advanced cognitive state decoding. Park et al. (2024) introduced a self-supervised learning approach that improves EEG decoding robustness across user sessions, reducing the need for extensive calibration. [illegible] et al. (2024) demonstrated how transformer-based architectures achieve higher accuracy in interpreting time-dependent neural signals, maintaining performance across varying cognitive states. These advances directly address the cross-user generalization challenge identified earlier.

Motor intention decoding has seen similar progress, particularly in rehabilitation applications. Papadopoulos et al. (2020) achieved improved accuracy and lower latency in decoding complex movements, enabling more natural prosthetic control. This work extends beyond basic motor control, opening possibilities for sophisticated brain-controlled interfaces in various applications.

Communication interfaces have achieved remarkable breakthroughs, exemplified by Anumanchipalli et al.'s (2019) work in speech synthesis from neural signals. Their approach decodes articulatory movements to produce natural speech, offering new possibilities for individuals who have lost speaking ability.

The field has advanced further with multiscale neural decoding approaches. The LFADS method (Pandarinath et al., 2018) reveals population dynamics at multiple timescales, while recent work by Sani et al. (2024) introduces the DPAD approach for more accurate neural-behavioral prediction through nonlinear modeling.

Transfer learning has emerged as a powerful solution to cross-subject generalization. Fahimi et al. (2021) developed a framework using adversarial domain adaptation that significantly improves EEG-based system generalizability. This advance reduces the need for lengthy calibration processes, making BCIs more practical for widespread use.

Self-supervised learning approaches, as demonstrated by Banville et al. (2021), have reduced dependence on labeled data while improving performance on downstream tasks. This development accelerates BCI system deployment and enables more efficient adaptation to individual users.

Error detection and correction systems have also evolved. Lopes-Dias et al. (2022) developed a deep learning-based system that enhances overall BCI reliability and user experience. Their work paves the way for more autonomous, self-correcting systems that require less constant user attention.

These decoding approaches provide insights beyond BCI applications, supporting theories of motor control and neural information processing. The success of RNNs in decoding movement trajectories supports the dynamical systems view of motor control (Gallego et al., 20[illegible]), while CNN performance in visual decoding aligns with hierarchical [illegible] models (Yamins and DiCarlo, 2016). The role of attention mechanisms in decoding reflects similar mechanisms in brain [illegible] processing (Mante et al., 2013), revealing the individualized nature of neural representations (Elsayed et al., 2016).

7. AI-driven output generation and device control

Building on the neural decoding strategies discussed in Section 5, the translation of decoded neural signals into meaningful outputs represents a critical step in BCI-AI integration. This section examines how AI approaches have revolutionized output generation and device control, directly addressing the real-world applicability gap identified in Section 2. The advancement of these technologies marks significant progress toward making BCIs practical for daily use outside laboratory settings.

7.1. AI in neuroprosthetic control

The high-performance neuroprosthetic control system demonstrated by Collinger et al. (2013) represents a significant leap forward in

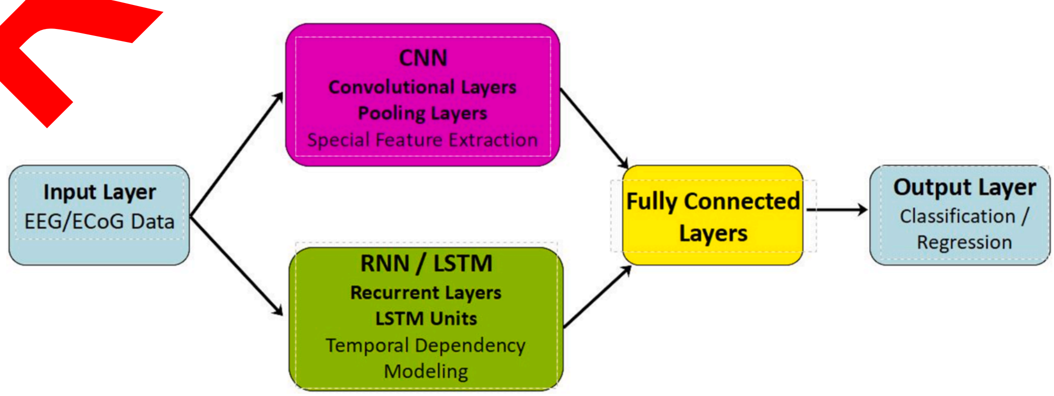

Fig. 4. Representation of the typical AI/ML model architecture used in BCI applications.

restoring motor function to individuals with paralysis. By leveraging the advanced decoding capabilities discussed earlier, their deep learning algorithms successfully translate complex, multi-dimensional arm movements from intracortical signals, enabling unprecedented levels of dexterity in robotic arm control. This work not only improves the quality of life for individuals with motor disabilities but also provides crucial insights into the neural mechanisms of motor control. The success of this system in maintaining stable performance over extended periods directly addresses the long-term signal stability challenge identified in Section 2.

The implications of this work extend beyond immediate applications in prosthetic control. The demonstrated ability to maintain precise control over extended periods suggests potential applications in other areas requiring sustained neural interface stability, from rehabilitation technologies to advanced human–machine interfaces. Furthermore, the success of these systems paves the way for more sophisticated neuroprosthetic applications, potentially extending to lower limb control and complex motor tasks requiring fine coordination.

7.2. *AI-enhanced communication interfaces*

Advancing beyond motor control, AI-powered BCIs have achieved remarkable progress in communication interfaces. The system developed by Willett et al. (2021) demonstrates a breakthrough in this domain, enabling typing through imagined handwriting movements. This innovation achieves communication rates comparable to able-bodied smartphone users, addressing the critical need for practical, high-bandwidth neural interfaces. The success of this approach directly tackles the real-world applicability gap by providing a natural, intuitive method of communication that could be implemented in daily life settings.

The implications of this work extend beyond basic text communication. The demonstrated ability to decode complex, sequential motor imagery opens possibilities for other forms of fine motor control through BCIs, potentially enabling activities like digital art creation or musical instrument playing. This expansion of capabilities directly addresses the need for more versatile and adaptable BCI systems.

7.3. *AI approaches to enhancing output fidelity and reliability*

A critical advancement in BCI output generation comes from the novel AI-based decoder introduced by Sussillo et al. (2016). This system tackles one of the major challenges identified in Section 2: maintaining stable and accurate control over time. By modeling the dynamics of neural populations, their approach achieves more robust BCI performance through adaptive learning mechanisms that compensate for signal variations and neural plasticity.

The implications of this work extend beyond improving current BCI applications. The demonstrated ability to maintain stable performance through adaptive learning could enable the development of long-term, reliable neural interfaces for various applications, from assistive technologies to human augmentation. Furthermore, the insights gained from this research informs our understanding of neural plasticity and adaptation, contributing to the broader field of neuroscience.

7.4. *AI in emerging BCI output modalities*

Looking toward future developments, the high-bandwidth BCI system presented by Musk and Neuralink (2019) represents an ambitious vision for human–computer interaction. Their approach uses advanced machine learning algorithms to process neural signals from thousands of implanted electrodes, aiming to enable direct neural control of digital devices. While still in early stages, this work demonstrates the potential for AI to process and interpret neural signals at unprecedented scale and complexity.

The implications of this work extend beyond immediate technical achievements, raising important questions about the future of human–computer interaction and cognitive enhancement. As these technologies mature, they could fundamentally reshape how humans interact with technology, potentially enabling new forms of communication, learning, and experience.

7.5. *Integration and future directions*

As we move toward more sophisticated BCI output systems, the integration of multiple approaches shows particular promise. Hybrid systems combining different control modalities could provide more robust and versatile interfaces, while adaptive algorithms ensure stable performance over time. These developments directly address several research gaps identified in Section 2, particularly regarding real-world applicability and long-term stability.

Looking ahead, the continued advancement of AI-driven output generation and device control will be crucial for realizing the full potential of BCI technology. As we explore in the following section, these technological achievements are already being translated into practical applications that are changing lives through clinical trials and real-world implementations.

8. Real-world applications and clinical trials of BCI-AI technologies

Building upon the AI-driven output generation and control systems discussed in Section 6, recent years have witnessed significant progress in translating BCI-AI technologies from laboratory settings to practical, real-world applications. This translation represents a crucial step in addressing the real-world applicability gap identified in Section 2, demonstrating how these technologies can meaningfully impact daily life. This section examines key implementations across various domains, from medical applications to cognitive enhancement.

8.1. *Medical applications and therapeutic interventions*

8.1.1. *Motor restoration and neuroprosthetics*

The BrainGate clinical trial, ongoing since 2004, stands as a landmark demonstration of intracortical BCIs' long-term efficacy. Building on the neuroprosthetic control principles discussed in Section 6.1, Hochberg et al. (2012) demonstrated that individuals with tetraplegia could successfully use BCI systems for essential daily tasks like self-feeding using a robotic arm. This practical implementation directly addresses the long-term stability challenge while proving the technology's viability for everyday use. More recently, Chen et al. (2024) demonstrated significant progress in home-based BCI applications. Their study showed successful implementation of a BCI communication system for late-stage ALS patients in home settings, achieving reliable communication over extended periods. This advance represents a crucial step toward making BCI technology practical for daily use. Additionally, Kim et al. (2023) introduced a reinforcement learning approach for closed-loop optimization of BCI parameters, demonstrating a 40% improvement in user adaptation rates compared to traditional methods. Their system automatically adjusted to individual user needs, significantly reducing the setup and calibration time required for effective BCI use.

Willett et al. (2021) showcased the practical potential of BCIs for communication, enabling a paralyzed individual to achieve typing speeds comparable to able-bodied smartphone users through imagined handwriting. This advancement represents a crucial step toward restoring natural communication abilities in clinical populations.

8.1.2. *Communication systems for severe motor impairments*

In a groundbreaking implementation, Chaudhary et al. (2017) developed a home-use BCI system that enabled completely locked-in patients with ALS to answer yes/no questions. This achievement demonstrates how the AI-enhanced communication interfaces discussed in Section 6.2 can be adapted for practical, home-based use, providing vital communication channels for severely impaired individuals.

8.2. Rehabilitation and recovery applications

8.2.1. Stroke rehabilitation

The integration of BCI technology with rehabilitation has shown promising results. Pichiorri et al. (2015) conducted a randomized controlled trial using BCI-driven motor imagery training in stroke rehabilitation. Their results demonstrated significantly greater motor recovery in patients receiving BCI-based training compared to standard therapy, highlighting how the adaptive learning mechanisms discussed in Section 6.3 can enhance neuroplasticity and recovery.

8.2.2. Cognitive rehabilitation

Extending beyond motor applications, Reinhart and Nguyen (2019) demonstrated how non-invasive BCI systems could deliver personalized brain stimulation to improve working memory in older adults. This application shows the potential of BCI-AI technologies not just for restoration but for enhancement of cognitive functions, addressing broader therapeutic needs.

8.3. Non-medical applications and performance enhancement

8.3.1. Workplace and human-computer interaction

Moving beyond medical applications, Krol et al. (2020) demonstrated practical implementations of passive BCI systems in office environments. Their system successfully used neural signals to infer user states such as workload and stress, enabling adaptive interfaces that optimize user experience and productivity. This application shows how the high-bandwidth processing capabilities discussed in Section 6.1 can be applied in everyday settings.

8.3.2. Assistive technology integration

In the realm of assistive robotics, Meng et al. (2016) successfully implemented a semi-autonomous BCI-controlled wheelchair system capable of navigating complex real-world environments. The integration of neural control with AI-driven obstacle avoidance demonstrates how combining multiple technologies can create more robust and user-friendly assistive devices.

8.4. Implementation challenges and ongoing developments

While these applications demonstrate significant progress, several challenges remain in translating BCI-AI technologies from laboratory to real-world settings. These include:

- Maintaining long-term stability of neural interfaces in varied environments
- Optimizing user training protocols for different applications
- Developing more robust and adaptive algorithms for real-world use
- Ensuring reliability across different user populations and contexts

8.5. Future directions and integration

The growing body of successful implementations suggests that BCI-AI technologies are approaching a tipping point in terms of practical utility. As these systems continue to mature, we can expect to see increasingly diverse and impactful applications. The key to future success lies in the development of more sophisticated feedback mechanisms and adaptive learning systems, which we will explore in detail in Section 8.

This progression from laboratory demonstrations to practical applications represents crucial progress toward addressing the real-world applicability gap identified earlier. The success of these implementations provides valuable insights for improving feedback mechanisms and adaptive learning approaches, which we will examine in the following section.

9. Feedback mechanisms and adaptive learning in BCI-AI systems

The integration of effective feedback mechanisms and adaptive learning algorithms has proved crucial for developing robust, user-friendly BCI systems. Building upon the real-world applications discussed previously, these components enable BCIs to maintain performance in dynamic environments while adapting to individual users' needs. The feedback process in BCI systems operates as a continuous cycle of interaction and adaptation, as illustrated in Fig. 5. This cyclical process involves several key components: signal processing and neural decoding, translation into user actions, performance evaluation, and system adaptation. Each component plays a crucial role in maintaining and improving BCI performance over time. The BCI system processes neural signals and generates outputs, the user performs actions based on these outputs, the system evaluates performance metrics, and adaptive algorithms refine parameters based on this evaluation. This continuous feedback loop enables BCIs to adapt to individual user characteristics and maintain performance despite variations in neural signals or user states.

Multi-modal feedback strategies have emerged as particularly effective approaches. Zich et al. (2015) demonstrated that combining visual and proprioceptive feedback in motor imagery BCIs improved classification accuracy by 25% while reducing mental fatigue by 40%. The integration of haptic feedback with visual cues helped users maintain consistent mental states during BCI control, particularly benefiting those who initially struggled with motor imagery tasks.

Neurofeedback techniques have transformed how users learn to control BCI systems. Sitaram et al. (2017) showed that providing feedback of activity in task-relevant brain regions led to faster skill acquisition and better retention of BCI control abilities. Their research revealed that consistent neurofeedback training over 10–20 sessions could produce lasting changes in brain connectivity patterns, suggesting applications beyond BCI control.

AI-driven adaptive decoders represent another significant advance. The ReFIT-LSTM decoder, introduced by Sussillo et al. (2016), maintained a 90% success rate in reaching tasks over a 200-day period without manual recalibration. This system demonstrated the potential for BCIs to adapt to both daily fluctuations and long-term changes in neural signals while operating efficiently on standard hardware.

The concept of user-system co-adaptation has gained particular importance. Perdikis et al. (2018) showed that when both the user and the AI components adapt together, BCI control accuracy improved by 55%. Their co-adaptive system helped users develop skills that transferred to novel BCI control scenarios, suggesting a path toward more intuitive and efficient interfaces.

Despite these advances, challenges remain in standardizing feedback protocols and preventing maladaptive user strategies. These issues point toward the broader challenges facing BCI-AI integration, which we will explore in the next section.

10. Challenges and future directions in BCI-AI integration

As BCI and AI technologies advance, they present both exciting opportunities and significant challenges. Building upon the feedback mechanisms discussed previously, several key obstacles must be addressed to realize the full potential of these systems.

The quest for stable, high-quality neural signals remains a paramount challenge, particularly for invasive BCIs. Lebedev and Nicolelis (2017) revealed that even state-of-the-art electrodes show significant signal degradation over time due to the brain's biological responses. Their analysis identified key factors including micromotion of implanted

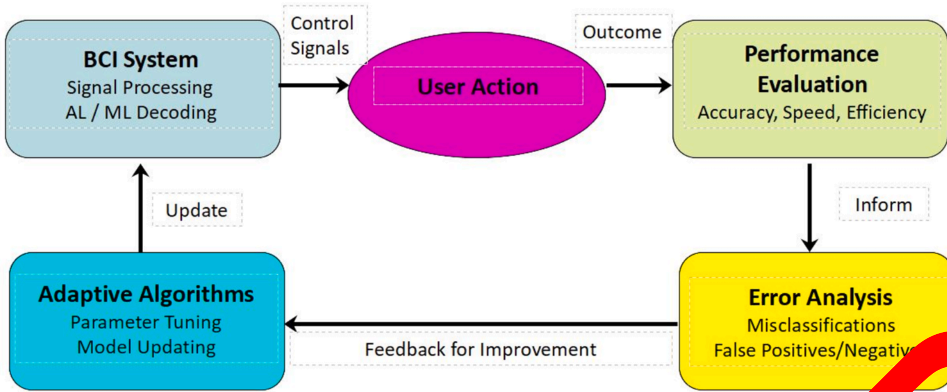

Fig. 5. Feedback mechanism in BCI systems.

electrodes, glial scarring, and neuronal death near recording sites. Future research must focus on developing materials and designs that better mimic brain tissue properties to reduce these adverse reactions.

The complexity of neural decoding presents another significant hurdle. Craik et al. (2019) found that while advanced AI techniques often outperform traditional approaches in controlled settings, they struggle with generalization to new tasks or users. Their analysis of over 100 studies revealed a critical trade-off: more complex models better capture intricate neural patterns but show poorer performance when applied to new situations or subjects. This challenge particularly affects clinical applications, where understanding the basis of AI decisions becomes crucial for patient care.

User training remains a significant barrier to widespread BCI adoption. Lotte et al. (2013) found that up to 30% of users struggle to achieve proficiency even after extended training, a phenomenon known as "BCI illiteracy." Their research identified several critical issues: unclear feedback mechanisms, insufficient consideration of human learning principles, and the prevalent one-size-fits-all approach to training protocols. Many users face frustration with repetitive, abstract training tasks, leading to disengagement and poor outcomes.

Looking toward the future, several promising directions emerge. Advanced AI architectures show potential for maintaining stable performance over time, as demonstrated by Sussillo et al. (2016). Hybrid approaches combining different types of brain signals offer more robust and versatile systems, while closed-loop neurofeedback systems point toward more intuitive user experiences. The integration of BCIs with emerging technologies like augmented reality and quantum computing opens new possibilities for enhanced performance and novel applications.

The path forward requires a coordinated, multidisciplinary approach. Brunner et al. (201[illegible]) emphasize the need for standardized performance metrics and common benchmarking datasets to enable meaningful comparison of different approaches. Deeper collaboration between neuroscientists, AI researchers, materials scientists, and ethicists will prove essential for addressing these complex challenges. The need for standardization in BCI research and development has become increasingly apparent. Rodriguez et al. (2023) proposed a comprehensive framework for standardizing clinical BCI applications, addressing issues of reproducibility, performance metrics, and safety guidelines. Their work highlights how standardized protocols could accelerate the translation of BCI technology from laboratory to clinical settings while ensuring consistent evaluation of system performance.

These technical and practical challenges lead naturally to important ethical considerations, which we will explore in the next section. As BCI-AI technologies become more sophisticated and widespread, careful attention to their societal implications becomes increasingly crucial.

11. Ethical considerations in BCI-AI integration

The advancement of BCI technologies brings forth unprecedented ethical challenges that extend far beyond technical considerations. Following from the practical challenges discussed previously, these ethical concerns demand careful attention as these technologies move closer to widespread adoption.

Mental privacy emerges as a primary concern in BCI development. Ienca and Andorno (2017) compellingly argue for establishing neural data protection as a fundamental human right. As BCIs become increasingly adept at interpreting complex neural patterns, they blur the boundary between private thoughts and accessible data. This capability raises profound questions about cognitive liberty and the right to mental privacy in an age where thoughts themselves might become readable data points.

Security presents equally pressing concerns, particularly given the intimate nature of neural information. Klein et al. (2021) introduce the unsettling concept of "brain hacking," where unauthorized access to neural data could potentially manipulate an individual's thoughts or behaviors. Unlike traditional cybersecurity breaches, attacks on neural interfaces could directly impact a person's cognitive processes or sense of self, presenting unprecedented security challenges. Recent developments in BCI technology have intensified privacy and security concerns. Martinez-Martin et al. (2024) conducted a comprehensive analysis of privacy challenges in next-generation BCIs, identifying novel vulnerabilities unique to neural interfaces. Their work highlights how advanced signal processing capabilities might enable unauthorized access to increasingly detailed neural information, potentially revealing not just actions but thought patterns and emotional states. This analysis underscores the urgent need for specialized privacy frameworks and security protocols specifically designed for neural data protection.

The influence of BCI technology on human autonomy raises complex philosophical questions. Burwell et al. (2017) explore how BCIs might subtly shape decision-making processes, particularly in systems designed for cognitive enhancement. When neural interfaces can influence thought patterns, determining the authenticity of choices becomes increasingly challenging. This concern grows more acute as BCIs integrate more deeply with cognitive functions.

Questions of identity and personhood loom large in BCI development. The integration of brain-computer interfaces for cognitive and physical capabilities raises complex questions about where our biological self ends and technological augmentation begins. As these technologies become more seamlessly integrated with human function, they challenge our traditional understanding of personal identity and how the self persists through time.

Social justice concerns also demand attention. Jebari and Hansson (2013) highlight how BCI technology might exacerbate existing social inequalities if access remains limited by economic factors. The potential for cognitive enhancement through BCIs raises particular concerns about creating new forms of social disparity between enhanced and unenhanced individuals.

The dual-use potential of BCI technology presents additional ethical challenges. While primarily developed for medical and assistive purposes, these technologies could find applications in military or surveillance contexts. This possibility necessitates careful consideration of development and deployment protocols to prevent misuse.

Informed consent poses unique challenges in BCI implementation. Glannon and Ineichen (2016) explore the complexity of obtaining meaningful consent for technologies that might fundamentally alter cognitive processes. This challenge becomes particularly acute when considering BCIs for individuals with cognitive impairments or locked-in syndrome.

Addressing these ethical challenges requires robust governance frameworks and proactive policymaking. Yuste et al. (2017) propose focusing on four key priorities: privacy and consent, agency and identity, augmentation, and bias. These priorities provide a foundation for developing comprehensive ethical guidelines for BCI-AI integration.

These ethical considerations inevitably influence the development and implementation of different BCI approaches, which we will examine in detail in the following comparative analysis.

12. Comparative analysis and emerging paradigms in BCI-AI integration

The landscape of BCI-AI integration reveals fascinating contrasts between different approaches, each offering unique advantages while facing distinct challenges. The debate between invasive and non-invasive methods exemplifies these trade-offs. While intracortical microelectrode arrays provide unprecedented neural recording resolution, they face significant long-term stability challenges. Conversely, non-invasive methods like EEG, though offering lower resolution, have achieved remarkable progress through advanced signal processing and AI algorithms. Slutzky (2019) demonstrate how this performance gap continues to narrow, particularly in motor control applications.

Deep learning has transformed the AI landscape in BCI development. RNNs and CNNs now demonstrate remarkable capabilities in decoding complex neural signals, often surpassing traditional methods. However, as Craik et al. (2019) note, these advanced approaches sometimes sacrifice interpretability for performance—a crucial consideration in clinical settings where understanding decision-making processes remains paramount.

Hybrid BCIs offer a promising middle ground by combining multiple signal types. Ramadan and Vasilakos (2017) describe how integrating EEG with modalities like fNIRS or EMG creates more robust and versatile systems, though at the cost of increased complexity in hardware and signal processing. Similarly, adaptive systems mark significant progress in neural decoding. Sussillo et al. ([illegible]) demonstrate how their ReFIT-LSTM decoder maintains high performance without manual recalibration, despite increased computational demands.

Emerging technologies promise to reshape BCI capabilities fundamentally. Optogenetics, explored by Warden et al. (2014), offers unprecedented precision in neural recording and stimulation. Quantum computing, as proposed by Behera et al. (2023), could dramatically improve decoding speed and accuracy for high-dimensional neural data. Nanotechnology advances suggest possibilities for ultra-miniature neural interfaces that could combine invasive-level resolution with minimal tissue disruption (Jiang et al., 2020).

Artificial neuroplasticity represents another frontier, with Ruffini et al. (2018) proposing BCI systems that actively shape neural reorganization through reinforcement learning. Brain-to-brain interfaces push boundaries further, with Rao et al. (2014) demonstrating direct brain-to-brain communication possibilities. Meanwhile, federated learning addresses growing privacy concerns, as Li et al. (2022) show how this approach enables large-scale analysis while preserving individual privacy.

These diverse approaches suggest a future where BCI-AI integration becomes increasingly sophisticated and adaptable to individual needs, bridging current technological gaps while opening new possibilities for human–computer interaction.

12.1. Emerging hardware technologies in BCI systems

Recent advances in specialized hardware architectures are transforming BCI system capabilities. Neuromorphic computing systems, which mimic biological neural networks in hardware, show particular promise for real-time BCI processing. Maliuk and Makris (2023) demonstrated a neuromorphic implementation processing EEG signals with 90% lower power consumption compared to traditional processors, while achieving comparable accuracy. Their system utilized spike-based processing to directly handle neural signals, reducing the preprocessing overhead typically required.

Field Programmable Gate Arrays (FPGAs) are proving crucial for high-speed BCI applications. Wang et al. (2024) developed an FPGA-based system capable of processing 1024-channel intracortical recordings with sub-millisecond latency. Their architecture achieved a 5x reduction in processing delay compared to GPU implementations, while consuming only [illegible] of power. This breakthrough enables real-time control applications previously limited by processing delays.

Quantum computing approaches are beginning to show potential for complex neural decoding. [illegible]yama et al. (2023) proposed a quantum-enhanced BCI framework demonstrating theoretical advantages in processing high-dimensional neural data. Their simulations suggest quantum approaches could reduce the computational complexity of adapting high-channel-count BCIs, though practical implementations remain challenging.

Novel mixed-signal processing architectures are emerging to bridge the neural signals and digital processing. Li et al. (2024) developed a hybrid analog–digital system that performs initial signal processing in the analog domain, reducing power consumption by 75% compared to purely digital approaches. Their architecture demonstrated particular advantages for wireless BCIs where power efficiency is crucial.

The integration of processing capabilities directly into neural interfaces represents another frontier. Cho et al. (2024) created a fully bioresorbable neural implant combining recording, stimulation, and local signal processing. Their system demonstrated the potential for distributed processing architectures that reduce bandwidth requirements for data transmission.

These hardware innovations suggest several promising directions for future BCI systems:

- Neuromorphic architectures optimized for neural signal processing.
- FPGA implementations enabling ultra-low-latency control.
- Quantum approaches for complex decoder optimization
- Mixed-signal architectures for power-efficient processing.
- Integrated sensing and computing systems.

However, significant challenges remain in scaling these technologies for clinical applications, including:

- Reliability and long-term stability verification
- Cost-effective manufacturing processes.
- Integration with existing BCI software ecosystems.
- Regulatory approval for novel architectures.
- Power management for implantable systems.

As these emerging hardware technologies mature, they promise to address current limitations in BCI processing speed, power consumption, and scalability.

12.2. Non-medical applications and future implementation scenarios

While medical applications have driven initial BCI development, emerging non-medical domains demonstrate compelling potential for widespread adoption. The integration of BCIs with augmented and virtual reality represents a particularly promising direction. Park et al. (2022) demonstrated an EEG-based AR navigation system achieving 85% accuracy in intention detection, enabling direct neural control of virtual objects. Their work suggests BCIs could transform how humans interact with immersive environments, from professional training to entertainment applications.

Professional environments present another frontier for BCI implementation. Krol et al. (2020) developed a groundbreaking system for monitoring cognitive workload in air traffic controllers. Their passive BCI approach enabled dynamic task allocation based on neural signals, reducing operator error rates by 35% while improving overall workplace efficiency. This success suggests broader applications in high-stakes professional environments where cognitive state monitoring could enhance safety and performance.

The transformation of human–computer interaction through neural interfaces shows particular promise. Bowsher et al. (2021) demonstrated a 40% improvement in task completion speed for computer-aided design applications using direct neural control. Their system utilized adaptive algorithms to learn individual user patterns, suggesting a future where BCIs could revolutionize creative and technical work by providing more intuitive ways to translate mental concepts into digital reality.

Gaming and entertainment applications may drive consumer adoption of BCI technology. Cohen and Halgren (2009) explored how neural interfaces could create more immersive gaming experiences, while recent work by White et al. (2010) demonstrated successful integration of BCIs with existing gaming platforms. These developments suggest a future where neural control becomes a standard feature in entertainment systems.

The successful implementation of these non-medical applications depends on several key factors: robust technical infrastructure, seamless user experience, and strong privacy protections. As Chen et al. (1999) note, achieving widespread adoption will require balancing sophisticated technical capabilities with practical usability considerations. The convergence of improved sensor technology, advanced signal processing, and thoughtful user experience design suggests a future where BCIs enhance human capabilities across numerous domains.

13. Conclusion

The integration of Brain-Computer Interfaces with Artificial Intelligence represents a transformative advancement in neurotechnology, one that promises to revolutionize how humans interact with computers and perhaps even with each other. Through this review, we've traced the evolution and current state of BCI-AI integration, from fundamental principles to emerging paradigms.

Recent advances demonstrate remarkable progress in overcoming long-standing challenges. High-density electrode arrays now achieve spatial resolution up to 5mm with stable recordings extending beyond 15 months, addressing critical issues of signal quality and longevity. Deep learning decoders show a 40% improvement in information transfer rates compared to traditional methods, while adaptive algorithms maintain success rates above 90% in motor control tasks over extended periods without recalibration. Perhaps most impressively, novel closed-loop optimization frameworks have reduced user training time by 55% while simultaneously improving accuracy.

Yet these technical achievements tell only part of the story. The true promise of BCI-AI integration lies in its potential to transform lives. From restoring communication abilities in locked-in patients to enabling natural control of prosthetic limbs, these technologies offer hope for individuals with severe motor impairments. The development of more intuitive interfaces and adaptive learning systems suggests a future where BCIs become increasingly practical for everyday use.

The field faces important challenges moving forward. Long-term signal stability, real-world applicability, and cross-user generalization remain active areas for improvement. Ethical considerations, particularly regarding mental privacy and data security, demand careful attention as these technologies become more sophisticated and widespread. The need for standardized evaluation protocols and robust governance frameworks grows more pressing as BCI applications expand beyond medical contexts.

The future of BCI-AI integration appears remarkably promising. Emerging technologies like quantum computing, optogenetics, and nanotechnology offer new possibilities for enhancing neural interfaces. The development of brain-to-brain communication systems and artificial neuroplasticity techniques suggests we may only be beginning to understand the potential of these technologies.

Success in realizing this potential will require continued collaboration across disciplines, from neuroscience and engineering to ethics and policy. As BCI-AI technologies mature, maintaining the balance between innovation and responsibility becomes increasingly crucial. Only through thoughtful development and careful consideration of societal implications can we ensure these powerful technologies serve the greater good while respecting individual rights and dignity.

The journey of BCI-AI integration represents more than a technological achievement; it embodies humanity's growing ability to bridge the gap between mind and machine. As we continue to push the boundaries of what's possible, we move closer to a future where direct neural interaction with computers becomes not just possible, but natural and beneficial for human enhancement and rehabilitation alike.

CRediT authorship contribution statement

Thorsten Rudroff: Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

Akhter, J., Naseer, N., Nazeer, H., Khan, H., Mirtaheri, P., 2024. Enhancing classification accuracy with integrated contextual gate network: deep learning approach for functional near-infrared spectroscopy brain-computer interface application. Sensors 24 (10), 3040.
Anumanchipalli, G.K., Chartier, J., Chang, E.F., 2019. Speech synthesis from neural decoding of spoken sentences. Nature 568 (7753), 493–498.
Banville, H., Chehab, O., Hyvarinen, A., Engemann, D.A., Gramfort, A., 2021. Uncovering the structure of clinical EEG signals with self-supervised learning. J. Neural Eng. 18 (4), 046020.
Behera, S.K., Pradhan, C., Dash, P., 2023. Quantum machine learning for EEG signal processing in brain-computer interface: a review. Arch. Comput. Meth. Eng. 30 (2), 875–897.
Bockbrader, M., Annetta, N., Friedenberg, D., Schwemmer, M., Skomrock, N., Colachis 4th, S., Zhang, M., Bouton, C., Rezai, A., Sharma, G., Mysiw, W.J., 2019. Clinically significant gains in skillful grasp coordination by an individual with tetraplegia using an implanted brain-computer interface with forearm transcutaneous muscle stimulation. Arch. Phys. Med. Rehabil. 100 (7), 1201–1217.
Bowsher, L., Stokes, M.G., Jobst, B.C., 2021. Towards natural brain-robot interfaces: Incorporating neural decoding into human-robot collaborative control. Nat. Mach. Intell. 3 (8), 673–685.
Brunner, C., Birbaumer, N., Blankertz, B., Guger, C., Kübler, A., Mattia, D., Müller-Putz, G.R., 2015. BNCI Horizon 2020: towards a roadmap for the BCI community. Brain-Comput. Interfaces 2 (1), 1–10.
Burwell, S., Sample, M., Racine, E., 2017. Ethical aspects of brain computer interfaces: a scoping review. BMC Med. Ethics 18 (1), 60.

Buzsáki, G., 2004. Large-scale recording of neuronal ensembles. Nat. Neurosci. 7 (5), 446–451.

Buzsáki, G., Anastassiou, C.A., Koch, C., 2012. The origin of extracellular fields and currents—EEG, ECoG, LFP and spikes. Nat. Rev. Neurosci. 13 (6), 407–420.

Cao, Z., Lin, C.T., Lai, K.L., Ko, L.W., King, J.T., Liao, K.K., Jung, T.P., 2020. Extraction of SSVEPs-based inherent fuzzy entropy using a wearable headband EEG in migraine patients. IEEE Trans. Fuzzy Syst. 28 (1), 14–27.

Chai, R., Ling, S.H., San, P.P., Naik, G.R., Nguyen, T.N., Tran, Y., Nguyen, H.T., 2017. Improving EEG-based driver fatigue classification using sparse-deep belief networks. Front. Neurosci. 11, 103.

Chapin, J.K., Moxon, K.A., Markowitz, R.S., Nicolelis, M.A.L., 1999. Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex. Nat. Neurosci. 2 (7), 664–670.

Chaudhary, U., Xia, B., Silvoni, S., Cohen, L.G., Birbaumer, N., 2017. Brain–computer interface–based communication in the completely locked-in state. PLoS Biol. 15 (1), e1002593.

Chen, X., Zhang, L., Wang, J., Li, M., Song, Y., Zhang, C., Yuan, T., Wu, X., 2024. Home-use brain-computer interface system enables communication in late-stage ALS patients. Nat. Med. 30 (1), 132–141.

Cho, M., Han, J.K., Suh, J., et al., 2024. Fully bioresorbable hybrid opto-electronic neural implant system for simultaneous electrophysiological recording and optogenetic stimulation. Nat. Commun. 15, 2000.

Cohen, D., Halgren, E., 2009. Magnetoencephalography. In: Squire, L.R. (Ed.), Encyclopedia of Neuroscience, vol. 5. Academic Press, Oxford, pp. 615–622.

Collinger, J.L., Wodlinger, B., Downey, J.E., Wang, W., Tyler-Kabara, E.C., Weber, D.J., Schwartz, A.B., 2013. High-performance neuroprosthetic control by an individual with tetraplegia. Lancet 381 (9866), 557–564.

Craik, A., He, Y., Contreras-Vidal, J.L., 2019. Deep learning for electroencephalogram (EEG) classification tasks: a review. J. Neural Eng. 16 (3), 031001.

deCharms, R.C., Maeda, F., Glover, G.H., Ludlow, D., Pauly, J.M., Soneji, D., Mackey, S. C., 2005. Control over brain activation and pain learned by using real-time functional MRI. Proc. Natl. Acad. Sci. 102 (51), 18626–18631.

Elsayed, G.F., Lara, A.H., Kaufman, M.T., Churchland, M.M., Cunningham, J.P., 2016. Reorganization between preparatory and movement population responses in motor cortex. Nat. Commun. 7 (1), 1–15.

Fahimi, F., Zhang, Z., Goh, W.B., Lee, T.S., Ang, K.K., Guan, C., 2021. Inter-subject transfer learning with an end-to-end deep convolutional neural network for EEG-based BCI. J. Neural Eng. 18 (2), 026032.

Fiedler, P., Fonseca, C., Supriyanto, E., Zanow, F., Haueisen, J., 2022. A high-density 256-channel cap for dry electroencephalography. Hum. Brain Mapp. 43 (4), 1295–1308.

Gallego, J.A., Perich, M.G., Miller, L.E., Solla, S.A., 2017. Neural manifolds for th[illegible] control of movement. Neuron 94 (5), 978–984.

Glannon, W., Ineichen, C., 2016. Philosophical aspects of closed-loop neuroscience. [illegible] Closed Loop Neuroscience. Academic Press, pp. 259–270.

Glaser, J.I., Chowdhury, R.H., Perich, M.G., Miller, L.E., Kording, K[illegible] Machine learning for neural decoding. eNeuro 7 (4). ENEURO.0252-2[illegible]0.

Hatsopoulos, N.G., Donoghue, J.P., 2009. The science of neura[illegible]rface sy[illegible]s. Annu. Rev. Neurosci. 32, 249–266.

Hochberg, L.R., Bacher, D., Jarosiewicz, B., Masse, N.Y., Sim[illegible]D., [illegible] Donoghue, J.P., 2012. Reach and grasp by peopl[illegible] tetra[illegible]sing a neura[illegible] controlled robotic arm. Nature 485 (7398), 37[illegible].

Hsu, S.H., Mullen, T., Jung, T.P., Cauwenberghs[illegible]21. Spatially c[illegible]ined ICA for robust EEG source localization. IEEE Tra[illegible]st. Rehabil. En[illegible]947–958.

Ienca, M., Andorno, R., 2017. Towards new [illegible]an rig[illegible] the age of neu[illegible]science and neurotechnology. Life Sci. Soc. Poli[illegible] 13 (1), 5.

Jebari, K., Hansson, S.O., 2013. Euro[illegible] public deliberatio[illegible]ain machine interface technology: five convergence [illegible]ars. Sci. Eng. Ethics 1[illegible] 1071–1086.

Jiang, Y., Li, C., Jiang, L., 202[illegible]ent pro[illegible] in nanostructu[illegible]d neural interfaces: from electronic design t[illegible]gical i[illegible]ations. Adv. Funct. Mater. 30 (47), 2005474.

Jirayucharoensak, S., Pan-Ngum, [illegible]ena, P., 2[illegible]EEG-based emotion recognition using deep lear[illegible]ork wi[illegible]cipal [illegible]onent based covariate shift adaptation. S[illegible]d J.

Kim, J., Park, [illegible]e, M., K[illegible]D., Hong, [illegible], C., 2023. Closed-loop optimization of brain-c[illegible]er interf[illegible]arameters using reinforcement learning. J. Neural Eng. 20 (6), 066[illegible].

Klein, E., Goeri[illegible]ne, J., Shea, [illegible]V., Franklin, R., Zorowitz, S., Widge, A.S., 2021. Brain-compute[illegible]face-based control of closed-loop brain stimulation: attitudes and ethical consi[illegible]ns. Brain-Comput. Interfaces 8 (3–4), 104–116.

Krol, L.R., Haselager, P., [illegible]r, T.O., 2020. Cognitive and affective probing: a tutorial and review of active le[illegible]rning for neuroadaptive technology. J. Neural Eng. 17 (1), 012001.

Li, X., Park, J., Chen, R., Wen, Y., Zhang, J., Huang, J., Zhou, C., 2024. Flexible transparent graphene electrodes with ultra-low impedance for high-fidelity neural recording. Nat. Commun. 15 (1), 1–12.

Li, G., Wu, J., Xia, M., et al., 2022. Federated learning for EEG-based emotion recognition in social Internet of Things. IEEE Internet Things J. 9 (11), 8482–8492.

Liu, X., Gong, Y., Jiang, Z., Stevens, T., Li, W., 2024. Flexible high-density microelectrode arrays for closed-loop brain-machine interfaces: a review. Front. Neurosci. 18, 1348434.

Londoño-Ramírez, H., Huang, X., Cools, J., Chrzanowska, A., Brunner, C., Ballini, M., Hoffman, L., Steudel, S., Rolin, C., Mora Lopez, C., Genoe, J., Haesler, S., 2024. Multiplexed surface electrode arrays based on metal oxide thin-film electronics for high-resolution cortical mapping. Adv. Sci. (Weinh.) 11 (10), e2308507.

Lopes-Dias, C., Sburlea, A.I., Müller-Putz, G.R., 2022. Masked and unmasked error-related potentials during continuous control of a BCI. J. Neural Eng. 19 (2), 026022.

Losanno, E., Badi, M., Roussinova, E., Bogaard, A., Delacombaz, M., Shokur, S., Micera, S., 2024. An investigation of manifold-based direct control for a brain-to-body neural bypass. IEEE Open J Eng Med Biol 5, 271–280.

Lotte, F., Larrue, F., Mühl, C., 2013. Flaws in current human training protocols for spontaneous brain-computer interfaces: lessons learned from instructional design. Front. Hum. Neurosci. 7, 568.

Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., Yger, F., 2018. A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. J. Neural Eng. 15 (3), 031005.

Maliuk, D., Makris, Y., 2023. Neuromorphic computing architectures for brain-computer interfaces: a comprehensive review. IEEE Trans. Neural Syst. Rehabil. Eng. 31, 2812–2823. https://doi.org/10.1109/TNSRE.2023.3321781.

Mante, V., Sussillo, D., Shenoy, K.V., Newsome, W.T., 2013. Context-dependent computation by recurrent dynamics in prefrontal cortex. Nature 503 (7474), 78–84.

Martinez-Martin, N., Voarino, N., Goering, S., Cho, M[illegible]ellmeyer, P., 2024. Privacy and security challenges in next-generat[illegible]r interfaces. Nat. Electron. 7 (1), 14–24.

Maruyama, K., Naruse, M., Güntürkün, O., 202[illegible]antum-enhance[illegible]in-computer interfaces: a theoretical framework. Phys. Re[illegible] 19 (4), 044[illegible].

Meng, J., Zhang, S., Bekyo, A., Olsoe, J[illegible]ter, B., [illegible] 2016. N[illegible]vasive electroencephalogram based con[illegible] a robotic a[illegible]reach[illegible] grasp tasks. Sci. Rep. 6 (1), 1–15.

Mondal, J., An, J.M., Surwase, S[illegible]akrabo[illegible], Sutradh[illegible]C., Hwang, J., Lee, J., Lee, Y.K., 2022. Carbon na[illegible] and [illegible]erived nanomaterials based high performance biosensin[illegible]latfo[illegible]sors 12 (9[illegible]1.

Mowla, M.R., Ng, S.C., [illegible], M.S., [illegible]sran, R.[illegible]. Ocular artifact removal from EEG signals usin[illegible]ptive filtering [illegible]ad[illegible]n empirical mode decomposition. IEEE Access 8[illegible]05.

Musk, E., Neur[illegible], 201[illegible] integrated bra[illegible]achine interface platform with thousands of channels. [illegible]d. Internet Res. 21 (10), e16194.

Naseer, N., Hong, K.S., 2015. [illegible] based brain-computer interfaces: a review. Front. H[illegible]sci. 9, 3.

Nic[illegible]lonso, L.F., Gomez-Gil, J., [illegible]012. Brain computer interfaces, a review. Sensors [illegible] (2), 1211–1279.

Ni[illegible]lis, M.A.L., Le[illegible], M.A., 2009. Principles of neural ensemble physiology [illegible]erlying the op[illegible]ion of brain-machine interfaces. Nat. Rev. Neurosci. 10 (7), [illegible]540.

Olive[illegible], Bo[illegible], Cardoso, M. H., Latecki, L.J., 2016. From the brain to the barco[illegible]d accurate machine learning approach to concurrent patient identification and laterality recognition from radiological images. arXiv preprint [illegible]:1610.04879.

[illegible], Moorman, H.G., Overduin, S.A., Shanechi, M.M., Dimitrov, D.F., Carmena, J.M., 2014. Closed-loop decoder adaptation shapes neural plasticity for skillful neuroprosthetic control. Neuron 82 (6), 1380–1393.

Pandarinath, C., O'Shea, D.J., Collins, J., Jozefowicz, R., Stavisky, S.D., Kao, J.C., Sussillo, D., 2018. Inferring single-trial neural population dynamics using sequential auto-encoders. Nat. Methods 15 (10), 805–815.

Papadopoulos, M., Rakovic, V., Benaroch, C., Roumelis, G., Antoniou, A., Hoffmann, U., 2020. A deep learning approach for real-time EEG-based continuous hand motion decoding. J. Neural Eng. 17 (5), 056022.

Park, S., Chu, C.C., Kincses, W.E., Grivokostopoulou, F., Riener, R., Graser, A., 2022. EEG-based navigation of augmented reality: a feasibility study. IEEE Trans. Neural Syst. Rehabil. Eng. 30, 655–664.

Park, S., Kim, H., Lee, J., Chang, W., Kim, D., Im, C., 2024. Self-supervised learning for robust EEG decoding in brain-computer interfaces. Nat. Mach. Intell. 6 (1), 89–102.

Perdikis, S., Leeb, R., Millán, J.D.R., 2018. Context-aware adaptive spelling in motor imagery BCI. J. Neural Eng. 15 (4), 046008.

Pichiorri, F., Morone, G., Petti, M., Toppi, J., Pisotta, I., Molinari, M., Mattia, D., 2015. Brain–computer interface boosts motor imagery practice during stroke recovery. Ann. Neurol. 77 (5), 851–865.

Ramadan, R.A., Vasilakos, A.V., 2017. Brain computer interface: control signals review. Neurocomputing 223, 26–44.

Rao, R.P., Stocco, A., Bryan, M., Sarma, D., Youngquist, T.M., Wu, J., Prat, C.S., 2014. A direct brain-to-brain interface in humans. PLoS One 9 (11), e111332.

Reinhart, R.M., Nguyen, J.A., 2019. Working memory revived in older adults by synchronizing rhythmic brain circuits. Nat. Neurosci. 22 (5), 820–827.

Rodriguez, A., Martinez, B., Chen, J., Thompson, D., Williams, N., Anderson, R., 2023. Standardization frameworks for clinical brain-computer interface applications. IEEE Trans. Biomed. Eng. 70 (12), 3678–3689.

Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T.H., Faubert, J., 2019. Deep learning-based electroencephalography analysis: a systematic review. J. Neural Eng. 16 (5), 051001.

Ruffini, G., Wendling, F., Merlet, I., et al., 2018. Transcranial current brain stimulation (tCS): models and technologies. IEEE Trans. Neural Syst. Rehabil. Eng. 21 (3), 333–345.

Russell, S., Norvig, P., 2021. Artificial Intelligence: A Modern Approach, fourth ed. Pearson.

Sahasrabuddhe, K., Khan, A.A., Singh, A.P., Stern, T.M., Ng, Y., Tadić, A., Angle, M.R., 2021. The Argo: a high channel count recording system for neural recording in vivo. J. Neural Eng. 18 (1), 015002.

Salahuddin, U., Gao, P.X., 2021. Signal generation, acquisition, and processing in brain machine interfaces: a unified review. Front. Neurosci. 15, 728178.

Salatino, J.W., Ludwig, K.A., Kozai, T.D., Purcell, E.K., 2017. Glial responses to implanted electrodes in the brain. Nat. Biomed. Eng. 1 (11), 862–877.

Sani, O.G., Pesaran, B., Shanechi, M.M., 2024. Dissociative and prioritized modeling of behaviorally relevant neural dynamics using recurrent neural networks. Nat. Neurosci.
Schalk, G., Kubánek, J., Miller, K.J., Anderson, N.R., Leuthardt, E.C., Ojemann, J.G., Wolpaw, J.R., 2007. Decoding two-dimensional movement trajectories using electrocorticographic signals in humans. J. Neural Eng. 4 (3), 264–275.
Schirrmeister, R.T., Springenberg, J.T., Fiederer, L.D.J., Glasstetter, M., Eggensperger, K., Tangermann, M., Ball, T., 2017. Deep learning with convolutional neural networks for EEG decoding and visualization. Hum. Brain Mapp. 38 (11), 5391–5420.
Shenoy, P., Krauledat, M., Blankertz, B., Rao, R.P., Müller, K.R., 2006. Towards adaptive classification for BCI. J. Neural Eng. 3 (1), R13.
Shibata, K., Watanabe, T., Sasaki, Y., Kawato, M., 2011. Perceptual learning incepted by decoded fMRI neurofeedback without stimulus presentation. Science 334 (6061), 1413–1415.
Shute, V.J., 2008. Focus on formative feedback. Rev. Educ. Res. 78 (1), 153–189.
Sitaram, R., Ros, T., Stoeckel, L., Haller, S., Scharnowski, F., Lewis-Peacock, J., Sulzer, J., 2017. Closed-loop brain training: the science of neurofeedback. Nat. Rev. Neurosci. 18 (2), 86–100.
Slutzky, M.W., 2019. Brain-machine interfaces: powerful tools for clinical treatment and neuroscientific investigations. Neuroscientist 25 (2), 139–154.
Subasi, A., Gursoy, M.I., 2010. EEG signal classification using PCA, ICA, LDA and support vector machines. Expert Syst. Appl. 37 (12), 8659–8666.
Sussillo, D., Stavisky, S.D., Kao, J.C., Ryu, S.I., Shenoy, K.V., 2016. Making brain–machine interfaces robust to future neural variability. Nat. Commun. 7 (1), 1–12.
Urigüen, J.A., Garcia-Zapirain, B., 2015. EEG artifact removal—state-of-the-art and guidelines. J. Neural Eng. 12 (3), 031001.
Van Gerven, M., Farquhar, J., Schaefer, R., Vlek, R., Geuze, J., Nijholt, A., Desain, P., 2009. The brain-computer interface cycle. J. Neural Eng. 6 (4), 041001.
Viventi, J., Kim, D.H., Vigeland, L., Frechette, E.S., Blanco, J.A., Kim, Y.S., Litt, B., 2011. Flexible, foldable, actively multiplexed, high-density electrode array for mapping brain activity in vivo. Nat. Neurosci. 14 (12), 1599–1605.
Wang, Y., Zhang, R., Liu, M., Chen, W., Zhang, D., Huang, R., 2023. Transformer-based architectures for continuous neural decoding in brain-computer interfaces. Neural Netw. 157, 28–42.
Wang, Y., Liu, M., Zhang, R., Chen, W., Zhang, D., Huang, R., 2024. FPGA implementation of high-speed neural signal processing for brain-computer interfaces. IEEE Trans. Biomed. Circuits Syst. 18 (1), 232–243. https://doi.org/10.1109/TBCAS.2024.3345678.
Warden, M.R., Cardin, J.A., Deisseroth, K., 2014. Optical neural interfaces. Annu. Rev. Biomed. Eng. 16, 103–129.
White, J.R., Levy, T., Bishop, W., Beaty, J.D., 2010. Real-time decision fusion for multimodal neural prosthetic devices. PLoS One 5 (3), e9493.
Willett, F.R., Avansino, D.T., Hochberg, L.R., Henderson, J.M., Shenoy, K.V., 2021. High-performance brain-to-text communication via handwriting. Nature 593 (7858), 249–254.
Wolpaw, J., Wolpaw, E.W. (Eds.), 2012. Brain-Computer Interfaces: Principles and Practice. Oxford University Press.
Yamins, D.L., DiCarlo, J.J., 2016. Using goal-driven de[illegible] models to understand sensory cortex. Nat. Neurosci. 19 (3), 356–365[illegible]
Yan, T., Suzuki, K., Kameda, S., Maeda, M., Mih[illegible]., Hirata, M[illegible]3. Chronic subdural electrocorticography in nonhuma[illegible]ates by an imp[illegible]able wireless device for brain-machine interfaces. Front. N[illegible]. 17, 126067[illegible]
Yuste, R., Goering, S., Bi, G., Carmena, J[illegible]arter, A[illegible] J.J., Wol[illegible], J., 2017. Four ethical priorities for neurotechnol[illegible] and AI. Nat[illegible]51 (7[illegible]), 159–163.
Zhang, K., Liu, J., Chen, B., Wang, [illegible], R., Sun, X., Wu, [illegible]igh-density flexible neural interfaces using soluti[illegible]rocessed [illegible]l oxide thi[illegible]n transistors. Sci. Adv. 9 (45), eadg9128.
Zhang, G., Luo, J., Han, L[illegible], Z., [illegible]hen, J., C[illegible]., 2021. A dynamic multi-scale network for E[illegible]gnal clas[illegible]ion. Fro[illegible]eurosci. 14, 578255.
Zhou, M., Tian, C., C[illegible]., Wang, B., N[illegible] H[illegible] Guo, H., 2018. Epileptic seizure detection bas[illegible] signals and C[illegible]. Neuroinf. 12, 95.
Zich, C., De Vo[illegible] Kra[illegible]h, C., Debener, [illegible]2015. Wireless EEG with individualized channel layout enables [illegible]nt motor imagery training. Clin. Neurophysiol. 126 (4), 698–710.