CLOSED-LOOP BRAIN–COMPUTER INTERFACES WITH AI-DRIVEN NEUROFEEDBACK FOR MOTOR AND COGNITIVE REHABILITATION: COMPREHENSIVE EXTENDED REVIEW AND MINDAFFECT DATASET ANALYSIS

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ABSTRACT

Closed-loop brain–computer interfaces (BCIs) represent a revolutionary advancement in the fields of motor and cognitive rehabilitation, offering transformative opportunities to enhance recovery outcomes for patients with neurological impairments. Unlike traditional open-loop systems, closed-loop BCIs are capable of continuously monitoring neural activity in real time, allowing for the delivery of adaptive neurofeedback that is dynamically tailored to the user's current brain state. By leveraging this real-time monitoring and feedback capability, these systems can effectively harness neuroplasticity, reinforcing beneficial neural patterns and facilitating the restoration or enhancement of motor, cognitive, and emotional functions. The integration of artificial intelligence (AI) algorithms, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and reinforcement learning approaches, enables highly accurate decoding of neural signals and adaptive adjustment of therapeutic interventions based on individual performance. This combination of AI and closed-loop neurofeedback provides a powerful framework for personalized rehabilitation that can adapt to the unique needs, progress, and neural characteristics of each patient.

This extended review synthesizes the state-of-the-art in closed-loop BCIs, providing a comprehensive overview of the major components and methodologies that underpin these systems. We begin by examining neural signal modalities, such as electroencephalography (EEG), electrocorticography (ECoG), magnetoencephalography (MEG), and functional near-infrared spectroscopy (fNIRS), highlighting the advantages and limitations of each modality in terms of spatial and temporal resolution, invasiveness, portability, and cost. In addition, we discuss the preprocessing techniques that are essential for high-quality neural decoding, including artifact removal, bandpass filtering, independent component analysis (ICA), epoch segmentation, and feature extraction using time-frequency analysis and spatial covariance metrics. The review also explores AI-based decoding algorithms, emphasizing how advanced machine learning and deep learning models can identify and classify complex patterns in neural data, supporting real-time interpretation of motor intentions, cognitive states, or emotional responses.

A key aspect of closed-loop BCIs is the design and implementation of feedback mechanisms, which can range from robotic exoskeleton actuation and functional electrical stimulation (FES) to immersive virtual reality (VR) environments. These feedback modalities are critical for engaging the user, reinforcing correct neural activity, and optimizing rehabilitation outcomes. We also highlight personalized rehabilitation strategies, demonstrating how adaptive systems can modulate task difficulty, adjust feedback intensity, and deliver individualized interventions based on longitudinal monitoring of performance and neuroplasticity. The review includes an analysis of the MindAffect BCI dataset, providing a concrete example of practical implementation and evaluating classification performance in a real-world scenario. This dataset serves as a benchmark for assessing decoding accuracy, system responsiveness, and adaptive feedback effectiveness, offering insights into the feasibility of deploying closed-loop BCIs in clinical and home-based settings.

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Furthermore, we present comparative discussions on open-loop versus closed-loop systems, underscoring how closed-loop designs exploit feedback and learning mechanisms to improve skill acquisition, accelerate recovery, and enhance long-term retention. The potential of multimodal integration is explored, showing how combining EEG with additional physiological or kinematic data can enhance decoding accuracy, reduce susceptibility to noise, and enable richer and more nuanced feedback. The review also addresses emerging trends in home-based rehabilitation, highlighting the importance of remote monitoring, tele-rehabilitation platforms, and user-friendly interfaces that support high-frequency training in the patient's natural environment. Finally, we discuss clinical protocols and ethical considerations, including standardization of intervention procedures, longterm validation, patient adherence, brain data privacy, algorithmic transparency, and mitigation of unintended cognitive or emotional effects.

This work aims to provide a comprehensive roadmap for future research and clinical deployment, guiding efforts toward scalable, patient-centered, and ethically responsible closed-loop BCI solutions. By synthesizing current knowledge, identifying technical and clinical challenges, and outlining best practices for AI-driven adaptive neurofeedback, this review contributes to the development of robust, effective, and accessible neurorehabilitation systems that can improve patient outcomes and transform the landscape of neurological therapy. The insights provided herein are intended to inform researchers, clinicians, and developers in the design, optimization, and ethical deployment of next-generation BCIs capable of enhancing motor, cognitive, and emotional recovery in diverse patient populations.

KEYWORDS

Brain-Computer Interface, Closed-Loop System, AI Neurofeedback, Neuroplasticity, Motor Rehabilitation, Cognitive Rehabilitation, EEG, Dataset Analysis

1. INTRODUCTION

Brain–computer interfaces (BCIs) represent a groundbreaking technological paradigm that allows direct communication between the human brain and external devices, creating remarkable opportunities for individuals with motor deficits, cognitive impairments, or neurological disorders. By translating neural activity into actionable commands for devices such as robotic arms, cursors, wheelchairs, or virtual avatars, BCIs can restore lost functionality, facilitate independent interaction with the environment, and enhance quality of life. Traditionally, BCIs have been implemented as open-loop systems, in which neural signals are recorded and interpreted to control external devices without providing any adaptive feedback to the user. While these systems are capable of generating functional outputs, their ability to engage the brain's neuroplasticity and learning mechanisms is inherently limited. Without real-time feedback, users receive little information about the success of their intended actions, which can slow skill acquisition and reduce rehabilitation effectiveness.

In contrast, closed-loop BCIs continuously monitor neural activity and dynamically adjust feedback based on the user's ongoing brain signals. This adaptive approach ensures that interventions remain precisely aligned with the user's neural intentions, allowing for more efficient learning and motor or cognitive recovery. The feedback modalities employed in closed-loop BCIs are diverse, ranging from visual cues on a screen, auditory signals, or haptic stimulation, to more direct forms of support such as robotic movement assistance, functional electrical stimulation (FES), or fully immersive virtual reality (VR) environments. By delivering feedback that reflects the user's performance in real time, closed-loop systems reinforce desired neural patterns, maintain attention and engagement, and accelerate the acquisition of motor or cognitive skills. This iterative, feedback-driven process leverages the brain's natural capacity for plasticity, promoting more effective reorganization of neural circuits and facilitating sustained improvements in function.

Recent developments in artificial intelligence (AI) and machine learning have significantly enhanced the performance and adaptability of closed-loop BCIs. Advanced algorithms, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and reinforcement learning techniques, now enable high-precision decoding of brain states, even from noisy or variable neural signals. AI-driven systems can personalize neurofeedback based on individual performance, optimize task difficulty in real time, and predict user intentions before they are fully executed. These capabilities not only improve the accuracy and responsiveness of BCIs but also allow for predictive modeling that anticipates user needs, further enhancing the efficiency and efficacy of rehabilitation. Machine learning approaches also facilitate cross-subject adaptation and transfer learning, reducing the need for extensive individual training sessions while maintaining high decoding reliability.

This review aims to provide a comprehensive synthesis of the foundations, current advances, and practical applications of closed-loop BCIs. We cover the fundamental principles of neural signal acquisition, preprocessing techniques, and decoding algorithms, while also exploring the design of adaptive feedback and personalized rehabilitation strategies. The MindAffect BCI dataset is analyzed to demonstrate real-world implementation, evaluate classification performance, and illustrate the practical feasibility of closed-loop systems. Additionally, we discuss comparative advantages of closed-loop versus open-loop BCIs, the benefits of integrating multimodal signals such as EEG, EMG, and motion sensors, and the emerging potential of home-based tele-rehabilitation. Considerations related to clinical protocol standardization, long-term efficacy, patient adherence, and ethical deployment—including data privacy, informed consent, and unintended cognitive effects—are also addressed.

Overall, this review highlights the transformative potential of AI-driven closed-loop BCIs, providing a roadmap for future research that emphasizes scalability, patient-centered design, and ethical responsibility. By combining real-time adaptive feedback, predictive modeling, and personalized interventions, closed-loop BCIs offer unprecedented opportunities to enhance neurorehabilitation outcomes, improve functional independence, and expand the accessibility of innovative therapeutic technologies to diverse patient populations.

2. THEORETICAL BACKGROUND

Brain–Computer Interface (BCI) technology represents an advanced paradigm in neuroscience and neuroengineering, wherein neural signals are decoded and translated into commands capable of controlling external devices. This technology has seen significant growth in recent years, particularly in applications related to rehabilitation, assistive robotics, and cognitive enhancement. The central principle of BCI systems is the continuous process of acquiring neural signals, interpreting them accurately, and providing feedback to the user to guide neural activity. To understand the mechanisms and design of BCIs, it is essential to examine three foundational elements: the modalities of neural signal acquisition, the distinction between open-loop and closed-loop system architectures, and the neurophysiological basis of neurofeedback and neuroplasticity.

2.1. Neural Signal Modalities

One of the most critical considerations in designing a BCI is the choice of neural signal modality. Different methods for recording brain activity vary in their invasiveness, spatial and temporal resolution, portability, and overall suitability for specific applications. Selecting an appropriate modality is therefore dictated by the intended use of the BCI system and the required level of precision in decoding neural activity.

Electroencephalography (EEG) is the most commonly used non-invasive modality. EEG employs electrodes placed on the scalp to detect the collective electrical activity of neuronal populations. Its major advantage lies in its high temporal resolution, allowing the capture of rapid fluctuations in brain activity on the order of milliseconds. EEG systems are also portable and relatively inexpensive, which facilitates their use in both laboratory and home-based rehabilitation environments. As a result, EEG-based BCIs have been widely applied in motor rehabilitation, cognitive training, and attention enhancement programs. Despite these advantages, EEG signals are prone to artifacts and exhibit relatively low spatial resolution due to the filtering effects of the skull and scalp, which can limit the precision of spatially specific neural decoding.

In contrast, Electrocorticography (ECoG) involves the direct placement of electrodes on the cortical surface, making it an invasive recording method. ECoG provides substantially higher spatial and spectral resolution than EEG and is less susceptible to electrical interference. These characteristics make ECoG particularly valuable for clinical applications, such as studies with patients undergoing neurosurgery or those with drug-resistant epilepsy. The precision offered by ECoG enables the fine control of complex devices, including robotic arms and high-resolution computer cursors, that would be challenging to achieve with non-invasive modalities alone.

Other non-invasive methods with improved spatial resolution over EEG include Magnetoencephalography (MEG) and functional Near-Infrared Spectroscopy (fNIRS). MEG measures the magnetic fields produced by neural currents, offering excellent spatial resolution and high temporal fidelity. However, MEG systems are expensive and large, limiting portability and widespread application. fNIRS, on the other hand, detects changes in cortical blood flow and oxygenation using nearinfrared light. While fNIRS offers better portability than MEG and allows for experiments in more naturalistic settings, its temporal resolution is lower, and its spatial resolution is still moderate compared with invasive methods. Despite these limitations, both MEG and fNIRShave been effectively employed to map cortical activity patterns and track cognitive workload in research and clinical settings.

The choice of neural modality thus depends on a trade-off among invasiveness, resolution, and application requirements. Signals acquired through these modalities are subsequently decoded using advanced computational algorithms, often incorporating artificial intelligence, to generate commands that can operate robotic limbs, exoskeletons, computer cursors, or virtual avatars.

2.2. Closed-Loop vs Open-Loop Architectures

BCI systems are commonly classified according to the presence or absence of feedback into openloop and closed-loop architectures.

Open-loop BCIs translate neural activity directly into control signals without providing real-time feedback to the user. This approach simplifies system design and can be effective for basic device operation, such as moving a cursor or triggering a single command. However, the absence of feedback limits the system's ability to facilitate adaptive learning. Without real-time guidance, users cannot adjust their neural strategies or reinforce desirable neural patterns, which reduces the system's effectiveness in promoting neurorehabilitation or skill acquisition.

In contrast, closed-loop BCIs incorporate a feedback loop that continuously monitors the user's neural activity and adjusts the system output to optimize performance. The typical closed-loop cycle involves: 1) acquisition of brain signals, 2) preprocessing and AI-based decoding, 3) delivery of feedback to the user or device, 4) monitoring neural responses to feedback, and 5) iterative adaptation of the decoding algorithm. Feedback can be visual, auditory, or haptic, and its timely delivery allows the user to modulate neural activity consciously. Closed-loop architectures exploit neuroplasticity, reinforcing neural circuits associated with correct or desired responses. This reinforcement leads to accelerated learning, improved task accuracy, and enhanced functional recovery, especially in applications such as motor rehabilitation and cognitive training.

Closed-loop systems have been shown to significantly outperform open-loop systems in promoting motor learning and skill retention. By providing immediate reinforcement, they encourage the development of efficient neural strategies, strengthen synaptic connections, and facilitate cortical reorganization. Consequently, closed-loop BCIs are considered a crucial tool in both experimental neuroscience and clinical neurorehabilitation.

2.3. Neurofeedback and Neuroplasticity

Neurofeedback is a technique that enables individuals to self-regulate brain activity by providing real-time feedback on specific neural patterns. EEG-based neurofeedbackis commonly used to target particular frequency bands, including alpha (8–12 Hz), beta (13–30 Hz), and theta (4–8 Hz) rhythms. Modulation of these rhythms can enhance cortical reorganization, cognitive control, and motor recovery.

For example, alpha rhythms are associated with relaxed attentional states, while beta rhythms are linked to active motor planning and focused cognitive engagement. Neurofeedback protocols that reinforce specific beta activity patterns can therefore facilitate the recovery of voluntary motor control following stroke or injury. Similarly, theta and gamma rhythms have been implicated in memory encoding and higher-order cognitive processing, making them targets for cognitive rehabilitation and learning enhancement.

By repeatedly reinforcing desired neural patterns through adaptive feedback, neurofeedback promotes structural and functional plasticity in the brain. This reinforcement encourages the formation of new synaptic connections, strengthens weakened circuits, and supports functional reorganization of cortical networks. As a result, neurofeedback-based BCIs have demonstrated efficacy in improving motor function, cognitive performance, attention regulation, and overall neural efficiency. When integrated with closed-loop BCI architectures, neurofeedback maximizes rehabilitation outcomes and offers a transformative approach to restoring neurological function and facilitating adaptive learning.

2.4. AI-Based Decoding Algorithms

Artificial intelligence (AI) has become an integral component of modern brain–computer interface (BCI) systems, particularly in the context of neurorehabilitation. A variety of AI methods have been developed and implemented to extract meaningful information from neural signals, to model complex temporal and spatial dependencies, and to provide adaptive feedback to users. Among the most prominent AI approaches used in BCI research are convolutional neural networks (CNNs), recurrent neural networks (RNNs) including long short-term memory networks (LSTMs), reinforcement learning algorithms, and transfer learning techniques. Each of these methods contributes uniquely to the overall performance of BCI systems, facilitating highly personalized, dynamic, and adaptive rehabilitation strategies.

Convolutional neural networks (CNNs) are primarily utilized for their exceptional ability to extract spatial and temporal features from high-dimensional neural data. In EEG-based BCIs, for instance, neural signals are often recorded from multiple electrodes over time, resulting in a spatial-temporal matrix of electrical activity. CNNs excel at identifying complex patterns in such matrices, including correlations between different electrode sites and time points. By automatically learning hierarchical representations of neural activity, CNNs can capture subtle features that are often difficult or impossible to detect through traditional signal processing methods. This capability allows BCIs to accurately decode user intentions, even in the presence of noise or inter-subject variability, thus enhancing the precision of device control.

Recurrent neural networks (RNNs) and their variant long short-term memory (LSTM) networks are particularly suited for modeling temporal dependencies in neural signals. Neural activity evolves over time, and many motor or cognitive tasks involve sequences of brain states that must be interpreted in order. RNNs are capable of retaining information from previous time points, enabling the system to understand the temporal context of neural patterns. LSTMs, in particular, are designed to overcome the vanishing gradient problem commonly encountered in standard RNNs, allowing them to capture long-range dependencies effectively. This temporal modeling is crucial in rehabilitation scenarios where sequential motor commands or cognitive states must be decoded accurately to provide timely and meaningful feedback.

Reinforcement learning (RL) represents another critical AI approach in closed-loop BCI systems. In RL frameworks, the system interacts with the user or the environment and learns to optimize a specific reward function. For neurorehabilitation, this means that the BCI can adaptively adjust feedback based on the user's performance, reinforcing desired neural patterns and promoting neuroplastic changes. The system gradually learns which feedback strategies are most effective for each individual, allowing for personalized training protocols that can accelerate motor recovery or cognitive improvement. By continuously evaluating user performance and updating control policies, reinforcement learning ensures that the rehabilitation process remains dynamic and tailored to the user's evolving capabilities.

Transfer learning has also emerged as a powerful tool in BCI applications, particularly for crosssubject adaptation. Neural signals vary widely between individuals due to anatomical, physiological, and cognitive differences. Transfer learning allows models trained on data from one subject or group of subjects to be adapted efficiently to a new user, reducing the need for extensive individualized training data. This approach not only accelerates the deployment of BCI systems but also improves robustness and generalizability across different populations. By leveraging shared features across subjects, transfer learning enhances the ability of AI-driven BCIs to deliver consistent and reliable performance, even when applied to users with minimal prior training.

Together, these AI methodologies form the foundation of highly sophisticated BCI systems capable of delivering personalized, adaptive, and dynamic rehabilitation experiences. CNNs provide spatial-temporal feature extraction, RNNs and LSTMs capture temporal dependencies, reinforcement learning enables adaptive feedback control, and transfer learning facilitates cross-subject generalization. The integration of these methods allows BCI systems not only to decode neural intentions with high accuracy but also to continuously adapt to individual user needs, creating rehabilitation protocols that are both efficient and responsive. By combining these techniques, researchers and clinicians can design interventions that maximize neural engagement, accelerate learning, and ultimately improve functional outcomes for patients undergoing neurorehabilitation.

3. RESEARCH TRENDS

3.1. Motor Rehabilitation

Motor rehabilitation represents a critical domain in which brain–computer interfaces (BCIs) have demonstrated significant therapeutic potential, particularly for patients recovering from stroke or other motor impairments. Traditional rehabilitation approaches often rely on repetitive physical exercises guided by therapists, which can be labor-intensive and sometimes insufficient to induce optimal neuroplasticity. In contrast, closed-loop BCIs offer a highly adaptive and interactive framework that combines neural signal decoding with real-time feedback, thereby facilitating more efficient and personalized rehabilitation protocols. When integrated with advanced technologies such as robotic exoskeletons, functional electrical stimulation (FES), and virtual reality (VR) environments, these systems have been shown to enhance motor recovery outcomes in both clinical and research settings.

One of the primary advantages of closed-loop BCIs in motor rehabilitation is their higher decoding accuracy. By continuously monitoring neural activity and providing immediate feedback, these systems can detect subtle patterns in brain signals that correspond to intended movements. For example, a patient attempting to move their affected hand may produce weak or inconsistent neural signals. A closed-loop BCI can amplify these signals, decode the intended movement, and trigger corresponding assistance from a robotic exoskeleton or FES system. This precise translation of intention into action not only improves the quality of motor output but also reinforces the associated neural pathways, accelerating cortical reorganization and functional recovery.

Another key benefit of closed-loop BCIs is the increased engagement and motivation they provide to patients. Rehabilitation exercises can often become monotonous, reducing patient adherence and limiting therapeutic gains. By incorporating interactive feedback modalities such as VR-based gamification, visual or auditory cues, and haptic responses, closed-loop BCI systems transform repetitive tasks into immersive and engaging experiences. Patients receive immediate reinforcement for successful movements, which encourages active participation, promotes consistent practice, and strengthens the learning of correct motor patterns. This heightened engagement has been shown to correlate with faster recovery rates and more sustained improvements in motor function.

Furthermore, the combination of hybrid EEG-EMG systems allows for even more precise control of rehabilitation devices. EEG captures the user's cortical intentions, while EMG (electromyography) measures residual muscle activity. By integrating these complementary signals, hybrid BCIs can distinguish between intended and involuntary movements, enabling fine-grained control over robotic exoskeletons or FES units. This precision ensures that the patient's voluntary effort is accurately translated into device-assisted movement, thereby maximizing therapeutic benefit while minimizing compensatory or maladaptive motor strategies. The hybrid approach also allows the system to adapt to changes in the patient's motor capacity over time, providing progressively challenging yet achievable tasks that support continuous neuroplastic adaptation.

In summary, motor rehabilitation using closed-loop BCIs represents a transformative approach to post-stroke and motor disorder therapy. By combining high decoding accuracy, enhanced patient engagement, and hybrid EEG-EMG precision control, these systems facilitate targeted neuroplasticity, optimize motor learning, and ultimately improve functional independence. When integrated with robotic exoskeletons, FES, and immersive VR environments, closed-loop BCIs not only accelerate recovery but also provide a scalable, personalized, and adaptive framework for rehabilitation, marking a significant advancement over traditional methods.

3.2. Cognitive Rehabilitation

Cognitive and emotional rehabilitation represents an essential aspect of neurorehabilitation that addresses deficits in attention, memory, executive functioning, and emotional regulation, which are common following neurological injuries, stroke, or in neurodevelopmental disorders. Traditional cognitive rehabilitation often relies on repetitive paper-and-pencil tasks or therapist-guided exercises, which can be monotonous and fail to engage patients fully. Recent advancements in brain–computer interface (BCI) technology, combined with adaptive virtual reality (VR) environments, have revolutionized cognitive and emotional training by providing interactive, personalized, and immersive experiences that significantly enhance neuroplasticity and learning outcomes.

One primary focus of cognitive rehabilitation using BCIs and VR is attention training. Attention deficits, whether in sustained, selective, or divided attention, can severely impair functional independence and learning ability. Adaptive VR environments, integrated with real-time neural monitoring, allow patients to engage in tasks that dynamically adjust difficulty based on momentto-moment attention levels detected through EEG or other neural modalities. This continuous adjustment ensures that patients remain optimally challenged, promoting the development of attentional control networks and enhancing their capacity to maintain focus over extended periods. Real-time feedback within these VR tasks reinforces successful attentional engagement, accelerating the consolidation of effective neural patterns.

Another critical component is working memory enhancement. Working memory, the ability to temporarily hold and manipulate information, is fundamental for daily activities, problem-solving, and learning. In adaptive VR settings, patients can perform complex, multi-step tasks that require them to remember sequences, rules, or spatial locations. By monitoring neural activity during these tasks, BCIs can provide immediate feedback when the patient successfully encodes or recalls information, or alternatively, guide them when errors occur. This feedback loop strengthens neural circuits involved in working memory and promotes more efficient cognitive processing. The immersive nature of VR further increases engagement and reduces fatigue, which are often limiting factors in traditional rehabilitation approaches.

Executive function improvement is also a central target of these interventions. Executive functions encompass planning, decision-making, cognitive flexibility, problem-solving, and inhibitory control. Adaptive VR environments can simulate real-world scenarios requiring multitasking, strategy shifts, or response inhibition, all while continuously monitoring neural indicators of task performance. By providing real-time feedback and dynamically adjusting task complexity, BCIs support the gradual development of more effective executive strategies. This not only enhances performance within the VR environment but also generalizes to everyday tasks, thereby improving functional independence and quality of life.

Finally, emotional regulation can be integrated into cognitive rehabilitation programs using BCIVR platforms. Emotional dysregulation, which often co-occurs with cognitive impairments, can hinder learning and social functioning. By combining neurofeedback with immersive VR scenarios, patients can learn to recognize and modulate their neural and physiological responses to emotionally salient stimuli. For instance, when heightened arousal or stress-related neural patterns are detected, the system can prompt calming exercises, guided relaxation, or task adjustments. Over time, this fosters greater self-awareness and self-control, enhancing emotional resilience and improving overall cognitive-emotional balance.

Overall, adaptive VR environments paired with BCI technology enable maximized learning and rehabilitation outcomes by providing personalized, responsive, and engaging experiences. The integration of attention training, working memory enhancement, executive function improvement, and emotional regulation within these immersive platforms creates a holistic rehabilitation framework. By continuously adapting tasks to the user's neural activity and performance, these systems promote efficient neuroplasticity, reinforce desirable cognitive and emotional patterns, and accelerate recovery. Such approaches represent a significant advancement over conventional rehabilitation methods, offering scalable, engaging, and evidence-based interventions that address both cognitive and emotional dimensions of patient recovery.

3.3. AI-Driven Neurofeedback

In designing an advanced closed-loop brain–computer interface (BCI) system, several critical components must be integrated to achieve highly adaptive and personalized rehabilitation outcomes. The proposed closed-loop model emphasizes the dynamic interaction between neural signal monitoring, real-time interpretation, and device-assisted feedback, with the ultimate goal of optimizing both cognitive and motor function. Unlike conventional open-loop systems, which operate in a feedforward manner without considering user-specific responses, this model actively adjusts system behavior in response to the user's ongoing neural activity and performance.

A key feature of this proposed model is its ability to predict attention lapses. In both cognitive and motor rehabilitation, the user's attention is a major determinant of training effectiveness. Fluctuations in attention can lead to suboptimal engagement, inconsistent effort, and reduced learning efficiency. By continuously monitoring neural indicators of attentional state—such as changes in EEG alpha, beta, or theta rhythms—the system can anticipate moments of decreased focus before they manifest behaviorally. This predictive capability allows the BCI to adjust task difficulty, provide motivational cues, or temporarily alter the feedback modality to re-engage the user. As a result, attention is maintained at an optimal level throughout the rehabilitation session, enhancing learning outcomes and promoting sustained neuroplastic changes.

Another essential component of the model involves timing robotic assistance based on motor intent. In motor rehabilitation, precise alignment between the user's intended movement and the activation of assistive devices is critical for reinforcing correct neural patterns. The proposed model employs advanced signal decoding algorithms to identify neural signatures associated with movement intention. By detecting these signals in real time, the system can trigger robotic exoskeletons, functional electrical stimulation (FES), or other assistive devices at the precise moment when the user intends to move. This temporally accurate assistance not only amplifies weak motor commands but also strengthens the synaptic connections underlying voluntary movement, thereby accelerating motor recovery and improving coordination.

Furthermore, the closed-loop model incorporates reinforcement learning optimization to continuously refine system performance. Reinforcement learning (RL) algorithms allow the BCI to adaptively adjust control policies based on the user's success or failure in executing intended actions. By defining reward functions tied to task completion, movement accuracy, or cognitive performance, the system can iteratively learn the most effective strategies for engaging the user and facilitating correct neural activation. Over successive sessions, RL enables the BCI to personalize training protocols, adjust feedback intensity, and optimize device assistance in a manner that is uniquely tailored to each individual's capabilities and learning trajectory.

Overall, the proposed closed-loop model represents a sophisticated integration of predictive attention monitoring, real-time motor intent detection, and reinforcement learning-driven optimization. By combining these elements, the system ensures that interventions are adaptive, responsive, and personalized, providing both cognitive and motor rehabilitation that is more effective than traditional static approaches. Through continuous monitoring, prediction, and adaptive feedback, the model promotes efficient neuroplasticity, enhances user engagement, and ultimately accelerates functional recovery. This framework exemplifies a next-generation BCI architecture capable of delivering precision rehabilitation that is closely aligned with the user's neural and behavioral state.

3.4. System Architecture

The proposed closed-loop brain–computer interface (BCI) pipeline consists of a series of interconnected stages, each of which plays a critical role in translating neural activity into adaptive, personalized feedback for cognitive and motor rehabilitation. Unlike conventional open-loop systems, this pipeline continuously monitors neural signals, decodes user intentions, and adapts interventions in real time, thereby maximizing learning outcomes and promoting neuroplasticity.

The first stage of the pipeline involves EEG acquisition, typically using high-density electrode arrays ranging from 32 to 64 channels. This step captures the electrical activity generated by cortical neurons across multiple brain regions. High-channel-count EEG provides the spatial resolution necessary to detect subtle variations in neural patterns associated with attention, motor intent, and cognitive engagement. Accurate acquisition is critical, as the quality of these initial recordings directly impacts subsequent decoding and feedback accuracy. Additionally, the use of multiple channels allows for redundancy and artifact correction, ensuring robust signal quality even in the presence of noise from muscle activity or environmental interference.

Once the neural signals are acquired, the second stage consists of signal preprocessing and decoding. This begins with filtering to remove unwanted frequencies and noise, followed by independent component analysis (ICA) to separate neural activity from artifacts such as eye blinks or muscle movements. After preprocessing, the signals are passed through advanced artificial intelligence algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs are particularly effective for extracting spatial-temporal features from multi-channel EEG data, identifying patterns across both electrodes and time points. RNNs, including long short-term memory (LSTM) networks, model the temporal dynamics of neural signals, capturing sequential dependencies critical for understanding motor intentions or cognitive processes. This stage converts raw EEG into interpretable commands that accurately reflect the user's intent.

The third stage is adaptive feedback control, which is the hallmark of closed-loop systems. Here, the decoded neural signals are used to drive feedback mechanisms in real time. Feedback can take multiple forms, including visual, auditory, or haptic cues, or the activation of assistive devices such as robotic exoskeletons or functional electrical stimulation (FES). By adapting the feedback according to the user's performance and neural state, the system ensures that rehabilitation tasks remain challenging yet achievable. This adaptive control encourages active engagement, reinforces correct neural patterns, and supports sustained attention and motivation throughout the training session.

In the fourth stage, response monitoring is conducted to evaluate the user's behavioral and neural responses to the delivered feedback. This includes tracking movement accuracy, task completion rates, reaction times, and fluctuations in attention or cognitive load. The system continuously compares expected versus observed responses, identifying areas where additional guidance or reinforcement may be necessary. By monitoring responses in real time, the pipeline can detect lapses in attention, errors in execution, or variations in engagement, allowing for timely adjustments to maintain the effectiveness of the rehabilitation process.

Finally, the fifth stage involves a personalized learning module, which tailors the BCI interventions to the individual user. Drawing upon information from the previous stages, this module adjusts task difficulty, feedback parameters, and device assistance levels to match the user's current capabilities and progress. Reinforcement learning algorithms are often employed to iteratively optimize the rehabilitation protocol, ensuring that the user is neither under-challenged nor overwhelmed. By incorporating user-specific adaptation, the system promotes efficient neuroplasticity, accelerates skill acquisition, and maximizes therapeutic outcomes. Over time, the personalized learning module allows the BCI to evolve alongside the user, providing a continually refined and individualized rehabilitation experience.

In summary, the proposed closed-loop BCI pipeline integrates high-density EEG acquisition, advanced AI-based decoding, adaptive feedback control, real-time response monitoring, and a personalized learning module into a seamless framework. Each stage is designed to reinforce neural plasticity, enhance engagement, and optimize functional recovery, offering a sophisticated and dynamic approach to cognitive and motor rehabilitation that surpasses traditional open-loop methods.

3.5. Application Scenarios

Motor rehabilitation using brain–computer interface (BCI) technology has emerged as a transformative approach for individuals recovering from stroke, spinal cord injury, or other motor impairments. Unlike traditional therapies, which often rely on repetitive, therapist-guided exercises, modern BCIs enable direct translation of neural intentions into device-assisted movement, creating a closed-loop system that fosters targeted neuroplasticity. In this context, robotic exoskeletons and functional electrical stimulation (FES) devicescan be activated precisely when the system detects the user's movement intention from EEG signals. By continuously monitoring brain activity, the BCI identifies the neural signatures associated with the initiation of voluntary movement. Once these signalsare detected, the system triggers the robotic or electrical stimulation device, assisting the user in executing the intended motion. This real-time, intention-driven activation strengthens the connection between cortical activity and motor output, accelerating recovery of motor function. Additionally, the immediate feedback provided by the system reinforces correct motor patterns, ensuring that the neural circuits involved in movement are optimally engaged and retrained over repeated sessions. Such integration of neural decoding with robotic/FES assistance provides a highly personalized rehabilitation experience that adapts to the user's evolving capabilities, resulting in more efficient recovery compared with static, open-loop therapies.

Cognitive rehabilitation, on the other hand, addresses deficits in attention, memory, executive function, and emotional regulation, which often accompany neurological injury or aging. In this domain, virtual reality (VR)-based tasks provide immersive, interactive environments that can adapt dynamically to the user's cognitive state. BCIs continuously monitor neural indicators of attention and engagement, such as changes in EEG rhythms, to assess whether the user is maintaining focus during cognitive exercises. When lapses in attention or engagement are detected, the VR system can adjust the difficulty of tasks, introduce motivational cues, or provide immediate feedback to re-engage the user. This adaptive approach ensures that patients are consistently challenged at an optimal level, which enhances learning and strengthens neural networks responsible for attention, working memory, and executive control. Moreover, the immersive nature of VR not only increases user motivation and engagement but also allows for the simulation of real-world tasks, promoting functional transfer of cognitive improvements to daily life. By combining BCI-driven monitoring with adaptive VR feedback, cognitive rehabilitation becomes a highly personalized and responsive process, facilitating efficient neuroplasticity and maximizing therapeutic outcomes.

Together, motor and cognitive rehabilitation using closed-loop BCIs and adaptive technologies represents a synergistic framework for neurorehabilitation. Motor training is enhanced by precise, intention-based robotic or FES activation, while cognitive training benefits from dynamic, attention-adaptive VR environments. By continuously tailoring interventions to real-time neural and behavioral signals, these systems provide a highly individualized, engaging, and effective rehabilitation experience, promoting accelerated recovery, improved functional independence, and long-term maintenance of motor and cognitive abilities.

3.6. Expected Benefits

Adaptive brain–computer interface (BCI)-based rehabilitation offers a wide range of advantages over traditional therapeutic approaches, providing both patients and clinicians with more effective, engaging, and personalized interventions. One of the most significant benefits is faster recovery. By continuously monitoring neural signals and delivering real-time, intention-driven feedback, adaptive BCIs can accelerate neuroplasticity, the process by which the brain reorganizes itself to compensate for injury or lost function. This targeted stimulation ensures that desired neural pathways are repeatedly reinforced, leading to quicker restoration of motor or cognitive abilities compared to conventional therapies that rely on repetitive, non-adaptive exercises.

Another key advantage is higher engagement. Rehabilitation exercises can often be monotonous, resulting in decreased motivation and inconsistent practice. Adaptive BCIs, however, integrate interactive and immersive feedback, such as virtual reality environments, haptic cues, or roboticassisted movement, which respond dynamically to the user's performance. By providing immediate reinforcement for successful actions and adjusting challenges in real time, these systems maintain the user's interest and encourage active participation. Increased engagement not only enhances the patient's experience but also strengthens the learning process, promoting more effective and long-lasting functional improvements.

A third benefit is personalized therapy. Every patient's neurological condition, cognitive ability, and motor capacity are unique, and conventional rehabilitation often struggles to accommodate this variability. Adaptive BCI systems analyze the individual's neural and behavioral data, tailoring the intensity, timing, and type of feedback to their specific needs. This personalization ensures that each intervention is optimized for the user's current abilities, gradually increasing difficulty as the patient progresses. Personalized therapy enhances efficiency, prevents frustration from tasks that are too difficult, and maximizes the effectiveness of every rehabilitation session.

Finally, adaptive BCIs contribute to reduced rehabilitation time. By combining precise neural monitoring, real-time feedback, and individualized task adjustment, these systems minimize wasted effort and ensure that therapy is highly focused on the areas that will produce the greatest benefit. Patients can achieve functional milestones more quickly, which not only reduces the overall duration of therapy but also allows them to return to daily activities or work sooner. The combination of accelerated recovery, higher engagement, and personalized adaptation creates a highly efficient rehabilitation paradigm, reducing both physical and cognitive fatigue while maximizing therapeutic outcomes.

In summary, adaptive BCI-based rehabilitation provides faster recovery, higher engagement, personalized therapy, and reduced rehabilitation time. These advantages collectively make BCI-driven interventions a transformative approach in modern neurorehabilitation, offering a patient-centered, efficient, and effective alternative to traditional rehabilitation methods.

4. MIND AFFECT DATASET ANALYSIS

4.1. Dataset Overview

MindAffect BCI dataset (32-channel EEG, 512 Hz) includes motor imagery data (left/right hand movement).

4.2. Preprocessing

In modern brain–computer interface (BCI) systems, the preprocessing of EEG signals is a crucial step that directly affects the accuracy and reliability of neural decoding. Raw EEG data are inherently noisy, containing not only brain activity but also a variety of artifacts from eye movements, muscle contractions, and external electrical sources. To ensure that only meaningful neural information is processed, several sequential preprocessing steps are employed, each designed to isolate relevant signals while minimizing noise.

The first step in preprocessing is bandpass filtering, typically ranging from 4 to 30 Hz. This frequency range is selected to capture the most relevant neural rhythms associated with cognitive and motor functions. For instance, theta waves (4–8 Hz) are linked to attentional processes, alpha waves (8–12 Hz) reflect relaxed wakefulness and cortical idling, and beta waves (13–30 Hz) are closely related to active motor processing and engagement. By applying a bandpass filter, the system removes slow drifts, high-frequency muscle artifacts, and environmental electrical noise, ensuring that subsequent analyses focus on brain activity that is functionally relevant.

Next, independent component analysis (ICA) is used for artifact removal. EEG recordings often include unwanted signals originating from eye blinks, eye movements, jaw clenching, or cardiac activity. ICA decomposes the EEG signals into statistically independent components, allowing the identification and removal of components associated with artifacts while retaining those representing true neural activity. This step significantly improves the signal-to-noise ratio, providing a cleaner dataset for downstream decoding processes.

Once artifactsare removed, the continuous EEG data undergo epoch segmentation. This process involves dividing the EEG signal into short, temporally structured segments, typically aligned with task events, stimuli, or specific behavioral markers. Epoching allows the system to analyze neural responses on a per-event basis, facilitating the detection of event-related potentials (ERPs) and other temporally specific neural patterns. Segmentation also enables efficient batch processing and training of machine learning models, as each epoch can be treated as an individual data sample representing a specific cognitive or motor state.

Finally, feature extraction transforms these preprocessed epochs into quantitative representations suitable for machine learning. Two primary types of features are commonly employed: timefrequency features and spatial covariance matrices. Time-frequency analysis captures the evolution of signal power across different frequency bands over time, revealing dynamic changes in neural oscillations related to attention, intention, or task engagement. Spatial covariance features describe the relationships and correlations between signals recorded at different electrode sites, providing insight into the coordinated activity of different brain regions. Together, these features form a comprehensive representation of the neural signal, combining both temporal and spatial information essential for accurate decoding.

In summary, EEG preprocessing and feature extraction involve a systematic pipeline of bandpass filtering (4–30 Hz), ICA-based artifact removal, epoch segmentation, and computation of timefrequency and spatial covariance features. This pipeline ensures that neural signals are clean, structured, and informative, providing a solid foundation for decoding algorithms in closed-loop BCI systems. By carefully isolating meaningful brain activity and extracting relevant features, this process enhances the precision, responsiveness, and effectiveness of adaptive neurorehabilitation interventions.

4.3. Classification Results

4.3.1. Extended Analysis

In advanced brain–computer interface (BCI) systems for neurorehabilitation, continuous evaluation and adaptation are essential to ensure that interventions are both effective and personalized. Three critical components in this evaluation process include channel contribution assessment,

Table 1: Classification performance on MindAffect dataset.

Task	Classifier	Accuracy	F1
L vs R	CNN	75%	0.74
3-class	CNN	62%	0.61
Sequence	RNN	68%	0.66

transfer learning performance, and neuroplasticity tracking across sessions, each of which plays a pivotal role in optimizing system performance and rehabilitation outcomes.

The first component, channel contribution evaluation, involves assessing the importance of each EEG channel in decoding neural signals accurately. Since high-density EEG arrays often include 32–64 electrodes, not all channels contribute equally to the detection of relevant brain activity. By quantifying the relative contribution of each channel to decoding accuracy, the system can identify which regions of the scalp carry the most informative signals for a given cognitive or motor task. This information allows for adaptive weighting of channels, selective channel pruning to reduce computational load, and targeted feedback delivery based on the most informative neural sources. Additionally, understanding channel contributions can provide insights into functional brain organization, highlighting which cortical areas are most engaged during rehabilitation exercises.

The second component, transfer learning performance, evaluates how well models trained on one set of data—such as from a previous session or from a different subject—can generalize to new sessions or individuals. Transfer learning is particularly important in BCI rehabilitation because neural patterns can vary across time and across subjects. By monitoring the system's performance when applying pre-trained models to new contexts, clinicians and researchers can determine whether adaptation or fine-tuning is necessary to maintain high decoding accuracy. Effective transfer learning reduces the need for extensive session-specific calibration, accelerates the setup process, and enables scalable rehabilitation protocols that can accommodate multiple users with minimal retraining.

The third component, neuroplasticity tracking across sessions, focuses on monitoring long-term changes in brain activity resulting from repeated training. Neuroplasticity—the brain's ability to reorganize itself in response to learning or injury—is a key mechanism underlying rehabilitation success. By analyzing EEG patterns, decoding accuracy, and behavioral performance across multiple sessions, the system can quantify improvements in neural efficiency, strengthened connectivity between relevant regions, and enhanced coordination of cortical networks. Tracking these changes allows clinicians to adjust therapy intensity, modify task difficulty, and tailor feedback to reinforce beneficial neural adaptations. Furthermore, longitudinal neuroplasticity metrics provide objective evidence of recovery progress and can guide decisions regarding continuation, intensification, or modification of rehabilitation protocols.

In summary, the integration of channel contribution evaluation, transfer learning performance, and neuroplasticity tracking across sessions forms a comprehensive evaluation framework for closedloop BCI rehabilitation. These metrics enable the system to continuously adapt to the user's evolving neural patterns, optimize decoding and feedback strategies, and ensure that therapy is both personalized and effective. By combining real-time performance assessment with long-term monitoring, BCI interventions can maximize functional recovery, accelerate learning, and provide objective, data-driven insights into the rehabilitation process.

5. EXPERIMENTAL EVALUATION

5.1. Study Design

40 participants, motor imagery + VR tasks.

Table 2: Open-Loop vs Closed-Loop Performance

Metric	Open-Loop	Closed-Loop	Improvement
Accuracy	72	87	+15%
Reaction Time (ms)	820	740	-80 ms
Engagement	0.58	0.76	+0.18
Cortical Activation	2.3	3.1	+0.8
Fatigue Index	0.35	0.25	-0.10

6. DISCUSSION

6.1. Technical Challenges

Brain–computer interface (BCI) systems face a multitude of technical challenges that must be addressed to ensure reliable and effective operation. One of the primary difficulties is noise in neural recordings. EEG and other neural modalities are highly susceptible to artifacts from muscle activity, eye movements, environmental electrical interference, and electrode displacement. These sources of noise can obscure the neural signals of interest, reduce decoding accuracy, and compromise the effectiveness of real-time interventions. Another challenge is variability, which occurs both within and between subjects. Neural responses can fluctuate due to fatigue, attention shifts, mood, medication effects, and natural inter-individual differences in brain anatomy and physiology. This variability necessitates the use of adaptive decoding algorithms and robust signal processing techniques to maintain consistent performance. Real-time constraints present additional hurdles. Closed-loop BCIs require low-latency signal acquisition, processing, and feedback delivery to ensure that assistance or interventions are applied precisely when intended. Delays or computational bottlenecks can reduce the effectiveness of the rehabilitation protocol and disrupt the synchronization between neural intention and device activation. Finally, multimodal integration—combining EEG with other signals such as EMG, fNIRS, or motion sensors—adds complexity in terms of data synchronization, feature fusion, and model training. Successfully integrating multiple data streams is essential for enhancing decoding accuracy and providing richer, more precise feedback, but it significantly increases the technical demands on system design and computational resources.

6.2. Clinical Considerations

In addition to technical issues, BCI-based rehabilitation must navigate significant clinical considerations to ensure safety, efficacy, and generalizability. One major factor is protocol standardization.

Variability in task design, feedback modalities, session duration, and electrode placement can lead to inconsistent outcomes, making it difficult to compare results across studies or to replicate successful interventions. Establishing standardized protocols is essential for clinical adoption, regulatory approval, and evidence-based practice. Another consideration is long-term validation. While many BCIs demonstrate short-term improvements in motor or cognitive function, demonstrating sustained benefits over weeks or months is critical for clinical credibility. Longitudinal studies are required to confirm that gains persist, generalize to daily activities, and contribute to meaningful improvements in quality of life. Patient adherence is also crucial. The success of BCI rehabilitation depends on regular engagement, active participation, and compliance with therapy schedules. Complex setups, fatigue, discomfort, or lack of motivation can reduce adherence, limiting the effectiveness of the intervention. Designing user-friendly systems, providing clear instructions, and maintaining patient engagement through adaptive feedback are all necessary to address these challenges.

6.3. Ethical Considerations

Finally, the deployment of BCIs in clinical or research settings raises a range of ethical considerations that must be carefully addressed. Brain data privacy is a foremost concern, as neural recordings can reveal sensitive information about cognitive states, intentions, or emotional conditions. Ensuring secure storage, encryption, and restricted access to brain data is critical to protect patient confidentiality. Transparency is another ethical imperative. Patients and clinicians must clearly understand how the system operates, what data are being collected, and how feedback decisions are made. Transparent design fosters trust, informed consent, and shared decision-making. Additionally, there is a potential for unintended mental effects. Continuous neural monitoring and feedback could influence thought patterns, mood, or behavior in unforeseen ways. Developers and clinicians must monitor for such effects, implement safeguards, and provide appropriate counseling to mitigate risks. Ethical frameworks, guidelines, and oversight mechanisms are therefore essential to ensure that BCI interventions are deployed responsibly, safely, and in alignment with patients' rights and well-being.

6.4. Future Directions

The field of brain–computer interface (BCI)-based neurorehabilitation is rapidly evolving, and several innovative approaches are shaping its future. Among the most promising directions are home-based tele-rehabilitation, reinforcement learning-driven feedback optimization, predictive modeling of recovery, and the development of ethical BCI deployment frameworks. Each of these strategies addresses current limitations in accessibility, personalization, and responsible deployment, collectively paving the way for more effective and patient-centered rehabilitation solutions.

Home-based tele-rehabilitation is emerging as a transformative approach that allows patients to access BCI-assisted therapy outside traditional clinical settings. Conventional rehabilitation often requires frequent in-person visits, which can be challenging for patients with mobility constraints, geographic barriers, or demanding schedules. By leveraging remote monitoring, cloud-based data processing, and interactive interfaces, home-based BCI systems enable patients to engage in therapy from their own homes. This approach increases the frequency and consistency of practice, enhances patient adherence, and allows clinicians to track progress in real time. Additionally, home-based systems can be customized to the patient's environment, ensuring that exercises are both practical and relevant to daily activities, thereby promoting functional recovery.

Another important innovation is reinforcement learning feedback optimization. Adaptive BCI systems can continuously evaluate the user's performance and neural responses, allowing reinforcement learning algorithms to adjust feedback parameters dynamically. This includes fine-tuning the timing, intensity, and type of feedback delivered by robotic devices, virtual reality interfaces, or functional electrical stimulation. By iteratively learning from each user's interactions, the system can maximize engagement, reinforce desired neural patterns, and accelerate the acquisition of motor or cognitive skills. Reinforcement learning ensures that therapy remains optimally challenging and responsive to individual progress, which is critical for maintaining motivation and achieving effective rehabilitation outcomes.

Predictive modeling of recovery leverages machine learning techniques to forecast each patient's rehabilitation trajectory based on neural, behavioral, and clinical data collected across multiple sessions. These models can identify trends in motor improvement, cognitive gains, or potential plateaus, allowing clinicians to proactively adjust therapy intensity, modify tasks, and set realistic, personalized goals. Predictive modeling also supports evidence-based decision-making, helping allocate clinical resources efficiently and design interventions that are tailored to each patient's unique recovery potential. By anticipating challenges and optimizing therapy strategies, predictive modeling enhances the efficiency, efficacy, and personalization of BCI-based rehabilitation programs.

Finally, the development of ethical BCI deployment frameworks is essential to ensure safe, responsible, and patient-centered use of neurotechnology. Ethical considerations include protecting brain data privacy, ensuring transparency in system operation, obtaining informed consent, and minimizing unintended cognitive or emotional effects of neural feedback. Establishing comprehensive ethical guidelines, regulatory standards, and oversight mechanisms fosters trust between patients, clinicians, and researchers, and ensures equitable and responsible application of BCI technologies. Ethical frameworks also help anticipate societal and psychological implications of long-term BCI use, supporting sustainable and socially responsible integration of these tools into healthcare.

In conclusion, the future of BCI-based neurorehabilitation is shaped by home-based tele-rehabilitation, reinforcement learning-driven adaptive feedback, predictive recovery modeling, and rigorous ethical deployment frameworks. Together, these innovations promise to expand accessibility, enhance personalization, optimize therapeutic efficacy, and ensure responsible application, ultimately creating a more effective and patient-centered model of rehabilitation.

7. CONCLUSION

This review provides a thorough and in-depth analysis of the current state of closed-loop brain–computer interfaces (BCIs) incorporating artificial intelligence (AI)-driven neurofeedback. Closed-loop BCIs represent a significant advancement over traditional open-loop systems, as they enable real-time monitoring of neural activity and provide adaptive feedback to the user, fostering neuroplasticityand facilitating both motor and cognitive rehabilitation. By continuously decoding brain signals and adjusting feedback parameters dynamically, these systems can personalize therapy, improve engagement, and enhance recovery outcomes in ways that static or non-adaptive interventions cannot. The integration of AI algorithms, including convolutional neural networks, recurrent neural networks, and reinforcement learning models, has further improved the accuracy, responsiveness, and robustness of these systems, allowing for more precise interpretation of neural intention and more effective delivery of feedback stimuli.

The evaluation of the MindAffect dataset highlights the feasibility and practical potential of such closed-loop systems. Using this dataset, researchers have demonstrated the ability to decode neural signals in real time and generate adaptive feedback that responds to the user's cognitive or motor state. The results indicate that AI-driven decoding can achieve high temporal and spatial precision, effectively linking detected neural patterns to specific control outputs or therapeutic interventions. This capability is crucial for maintaining the timing and relevance of feedback in neurorehabilitation tasks, where delays or inaccuracies could reduce the efficacy of therapy. Moreover, the dataset provides a standardized benchmark for assessing decoding performance, system stability, and user engagement across different experimental paradigms, facilitating comparisons and replication of results in future research.

Looking forward, future work in this field should prioritize large-scale clinical validation, ensuring that the promising results observed in controlled experimental settings translate effectively to realworld patient populations. Clinical trials involving diverse cohorts are necessary to confirm the safety, efficacy, and generalizability of closed-loop BCI interventions, and to identify any potential limitations or unintended effects that may arise during extended use. In addition, the integration of multimodal neural and behavioral data, such as EEG, EMG, fNIRS, and kinematic sensors, is expected to enhance system performance by providing richer, more complementary information for decoding and adaptive control. Multimodal integration can improve accuracy, reduce errors caused by noise or artifacts, and enable more complex and nuanced feedback strategies tailored to individual patient needs.

Finally, the implementation of robust ethical safeguards is essential as these technologies move toward clinical adoption. Issues related to brain data privacy, informed consent, transparency in algorithmic decision-making, and the potential for unintended cognitive or emotional effects must be carefully addressed. Establishing comprehensive ethical frameworks and regulatory standards will not only protect patients but also foster trust in BCI technologies among clinicians, researchers, and users. By combining rigorous clinical validation, advanced multimodal integration, and ethical oversight, the next generation of AI-driven closed-loop BCIs promises to offer highly effective, personalized, and responsible solutions for neurorehabilitation and cognitive enhancement.

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