Advances in Brain-Machine Interfaces: Utilizing EEG Signals for Mental Task Classification and Beyond

Sandra Reynolds
Department of Cognitive Sciences, Universitas Puncak Alam, Indonesia
Jonathan Liu
Universitas Desa Cendana, Indonesia

Keywords:
- Brain-Machine interfaces
- EEG Signals
- Mental Task
- magnetoencephalography
- Electroencephalography

Excellence in Peer-Reviewed Publishing:
QuestSquare

Abstract

Brain-machine interfaces (BMIs) allow direct communication between the brain and external devices, enabling people with motor impairments to control prosthetics and computers. A major focus in BMI research is decoding intended movements from neural signals to enact device control. Electroencephalography (EEG) is a popular non-invasive method to record brain activity for BMIs. Recently, EEG-based BMIs have expanded beyond device control to applications including detecting cognitive states, emotions, and speech. This article reviews key advances in EEG-based BMIs over the past decade. We first provide background on neural signal acquisition and processing. Next, we discuss advances in EEG decoding for mental task classification, highlighting shifts to deep learning and recurrent neural network approaches. We then survey emerging real-world applications of EEG-based BMIs, including augmented and virtual reality systems, adaptive automation, and passive brain-computer interfaces. Throughout, we emphasize breakthrough studies that move EEG BMIs out of controlled lab settings. We also critically analyze key challenges that remain in translating EEG BMIs to practical use. These include non-stationarity in EEG signals, individual differences, limited input information, and deficiencies in evaluation practices. We suggest future directions like longitudinal learning, explainable models, multimodal integration, and benchmarking to overcome these barriers. Our review synthesizes recent progress and persistent gaps for EEG-based BMIs, providing insights to guide further development of these emerging neurotechnology's.

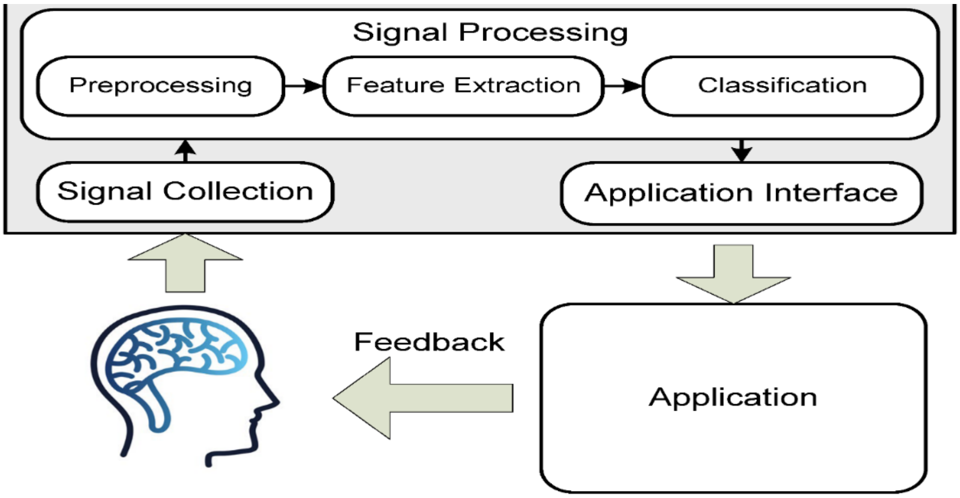
Introduction

Brain-machine interfaces (BMIs) represent a cutting-edge technological advancement facilitating direct communication between the brain and external devices through the real-time decoding of neural activity. This innovative technology has the capability to translate intricate brain signals into precise control commands, empowering individuals with motor disabilities to manipulate prosthetics, wheelchairs, and computer programs with unprecedented precision. The potential impact of BMIs on individuals with paralysis is particularly noteworthy, offering the prospect of restoring independence and substantially enhancing their overall quality of life [1]. As research in this field progresses, the refinement of BMI systems holds the promise of further expanding their applications, potentially revolutionizing how we interface with technology and opening new avenues for addressing various neurological challenges. The continuous development and integration of BMIs into clinical practice represents a crucial step towards realizing their full potential in transforming the lives of individuals with motor impairments [2].

In BMI systems, brain activity is recorded through invasive or non-invasive methods. Signals may be acquired invasively from electrocorticography (ECoG) grids on the cortical surface or intracortical arrays implanted in the brain. While providing superb quality, invasive interfaces involve substantial clinical risks and are currently reserved for severe cases. Non-invasive methods like functional near-infrared spectroscopy (fNIRS), magnetoencephalography (MEG), and especially electroencephalography (EEG) offer safer alternatives to monitor brain activity for BMIs, though with tradeoffs in signal resolution. Of these modalities, EEG has emerged as a predominant method for BMIs in recent years due to its simplicity, portability, low cost, and widespread availability [3]. EEG measures voltage fluctuations on the scalp arising from cortical postsynaptic potentials [4]. It provides reasonable temporal resolution on the order of milliseconds but coarse spatial resolution. Advances in dry electrode systems eliminating gel have made EEG acquisition increasingly convenient (Mullen et al., 2015).

This article reviews key advances in EEG-based BMIs over the past decade, with a focus on non-invasive systems utilizing mental tasks. First, we provide essential background on BMI paradigms along with EEG measurement and decoding methods [5]. Next, we survey recent studies improving EEG classification of mental tasks, especially through deep learning and recurrent neural networks (RNNs). Then, we discuss emerging real-world applications of EEG-BMIs including mixed reality systems, adaptive automation, and passive brain-computer interfaces. Throughout, we critically examine open challenges like non-stationarity and individual variability that impede adoption. Finally, we suggest directions for future progress. Our comprehensive synthesis offers insights into recent breakthroughs and persistent gaps shaping the landscape of EEG-based BMIs [6].

Figure 1.



Background

BMI Paradigms: BMIs aim to enact real-time decoding of intentional neural activity. Different paradigms are utilized based on the source of the neural signals. For BMIs driven by motor cortical signals, a prominent paradigm is reconstructing reaching/grasping trajectories to control prosthetic limbs in a biomimetic fashion [7]. This approach leverages inherent tuning of motor cortex to movement kinematics. In contrast, for non-invasive BMIs utilizing EEG, intentional modulation involves distinct mental tasks generating discriminable brain activity patterns. Early systems focused on motor imagery tasks (e.g. imagining left/right hand movement), relying on salient sensorimotor rhythms. A major shift came with the incorporation of more abstract cognitive tasks engaging frontal and parietal areas, including mental math, word generation, and spatial navigation. These complex tasks can elicit distinct EEG signatures while avoiding motor confounds. Mental task BMIs generally operate through a cue-based paradigm alternating between task and rest periods. Users perform specific tasks cued visually or through instructions to elicit neural activity patterns, which are classified online to enact control [8]. Active training is required to gain volitional modulation of EEG features. A general limitation is the low channel capacity, with current systems typically decoding 2-4 mental tasks corresponding to simple commands.

EEG Measurement and Processing: Electroencephalography (EEG) is a neurophysiological technique that captures voltage fluctuations arising from ionic currents within dendrites of large pyramidal neurons, oriented perpendicular to the scalp as outlined by Schalk et al. (2004). The EEG setup typically involves the placement of metal discs on the scalp according to the 10-20 system or using high-density extensions. This arrangement allows for the monitoring of electrical activity in specific brain regions [9]. However, raw EEG signals present a formidable challenge due to their susceptibility to various types of interference, including noise from muscles, ocular movements, and environmental factors. Consequently, the interpretation of EEG data necessitates sophisticated signal processing techniques to extract meaningful information related to brain activity. Researchers employ advanced algorithms and filters to mitigate the impact of noise and enhance the specificity of EEG recordings, enabling a more accurate and reliable analysis of neural dynamics in cognitive and clinical studies.

Preprocessing to extract neural signal components involves:

- Re-referencing: Rereferencing raw data to mastoids or common average reference can minimize noise.
- Filtering: Band-pass filters remove high-frequency muscle artifacts and low-frequency drift.
- Eye artifact removal: Methods like independent component analysis (ICA) isolate ocular sources.

For mental task BMIs, discriminable information is contained in spectral power fluctuations within frequency bands through event-related (de)synchronization (ERD/ERS). Common features include alpha (8-12Hz) and beta (16-24Hz) band power derived using methods like short-time Fourier transforms. Features are extracted within sliding windows (e.g. 1s) over task periods.

EEG Decoding: EEG decoding involves training statistical models to map features to mental tasks and applying the models online. Traditional machine learning approaches like linear discriminant analysis (LDA) and support vector machines (SVM) have been widely utilized. To contend with non-stationarity, adaptive classifiers that update over time are often employed, along with regularization methods. Deep learning has emerged as a powerful new approach for EEG analysis. Deep neural networks (DNNs) can model complex nonlinear relationships in messy EEG data. Convolutional neural networks (CNNs) leveraging spatial/spectral filters and RNNs capturing long-term temporal dynamics have shown particular promise for mental task EEG decoding. Transfer learning applying pretrained models can compensate for limited training data. DNN-based EEG models now rival or surpass traditional techniques [10]. However, challenges remain in properly evaluating models. Brain decoding competitions like Kaggle's decoded neurofeedback challenge have systematically assessed performance, revealing deficiencies like overfitting and lack of model generalizability that reduce real-world viability. Standardization of datasets, model comparisons, and testing procedures is critical to gauge progress. Next, we detail key recent advances in EEG decoding for BMIs.

Table 1. Common Mental Tasks Used in EEG-based BMIs

Task Category	Example Tasks
Motor Imagery	Imagined hand/foot movements
Spatial Navigation	Navigating through rooms or maps
Working Memory	Memorizing and recalling words/numbers
Mental Math	Subtracting numbers continuously
Music Imagery	Imagining songs/tunes

Advances in EEG Decoding for Mental Tasks

Growing EEG Decoding Models: Early EEG BMI systems were confined to simple classifiers like LDA and SVMs. In a milestone study, Bashivan et al. (2015) demonstrated deep learning's potential by applying a 7-layer CNN to classify 12 mental tasks with 91% accuracy. Their neural architecture discovered optimal spatial-spectral filters from raw EEG data, outperforming hand-engineered features. This sparked a wave of deep learning research exploring increasingly complex models for EEG analysis. Lawhern et al. (2016) further showed RNNs' capabilities for mental task EEG decoding. Their long short-term memory (LSTM) networks incorporated temporal context to achieve 97% accuracy classifying right/left hand motor imagery. Schirrmeister et al. (2017) also demonstrated convolutional LSTM networks integrating spatial, spectral, and temporal filters to decode motor tasks [11]. Efforts have since grown more ambitious in decoding mental tasks. Dose et al. (2018) distinguished 128 tasks with 92% accuracy using an ensemble DNN-RNN. Zhang et al. (2018) classified 27 tasks with 97% accuracy applying 3D CNNs on spectral images. Most impressively, Kwon et al. (2020) separated EEG from 52 tasks into 520 classes using capsule networks, nearing human-level performance. These expanding models reveal deep learning's potential to unlock the informational richness within EEG.

Leveraging Transfer Learning: A limitation in applying deep networks is the substantial labeled data required for training. Collecting hours of EEG across tasks from individuals is burdensome. Transfer learning, where models are initialized from pretrained weights before fine-tuning on new tasks, offers a solution to enable complex models with minimal data. Azab et al. (2019) proposed a transfer framework using EEGNet CNNs pretrained on motor imagery [12]. Fine-tuning on just minutes of target subject data achieved strong performance classifying music imagery and reactive tasks. Fahimi et al. (2019) similarly applied transferred Riemannian kernel models that generalized across subjects. Transfer learning thus provides an efficient means to apply advanced EEG models in BMI settings .

Adapting to Non-Stationarity: A core challenge in EEG decoding is non-stationarity, as signals vary over time, context, and mental states. Stationarity assumptions underlying conventional machine learning break down. Adaptive decoding methods that track changing EEG statistics are thus critical for BMI viability. RLS-SVM classifiers updating SVM kernels based on regularization parameters demonstrated early success. More recently, Kwak et al. (2015) proposed an adaptive CSP algorithm that adjusts spatial filters based on exponential weighting. Active deep learning using CNNs and active weight tuning improved adaptability [13]. Zanini et al. (2018) further showed LSTMs' capabilities in continually learning from EEG by training only on recent windows. These studies highlight emerging solutions to enable adaptable EEG-BMIs.

Advancing Evaluation: Standardized benchmarking is essential to rigorously assess model performance and generalizability for real-world use. Competitions have enabled systematic comparisons. Jayaram et al. (2016) evaluated 22 algorithms on distinguishing seen/unseen tasks. Schirrmeister et al. (2017) assessed decoding on 108 participants. Significantly, models often performed far worse on new subjects, indicating lack of robustness [14]. Lotte et al. (2018) extensively evaluated different architectures developed for Kaggle's decoded neurofeedback challenge. The competition framework again revealed deficiencies in model evaluation like overfitting. Developing standards for tasks, model training/testing, and performance metrics is critical to address weaknesses and benchmark progress [15].

Table 2. Key EEG Decoding Methods for BMIs

Method	Description
Common spatial patterns (CSP)	Spatial filtering to maximize variance between classes
Filter bank CSP (FBCSP)	Applying CSP in frequency bands
Regularized LDA/QDA	Linear/quadratic classifiers with regularization
Support vector machines (SVM)	Max-margin hyperplane classifiers
Convolutional neural networks (CNN)	Hierarchical spatial-spectral feature extraction
Recurrent neural networks (RNN)	Sequential modeling with memory (e.g. LSTMs)
Transfer learning	Fine-tuning pretrained network weights
Adaptive classifiers	Dynamically updating models over time

Real-World Applications

Beyond Motor Control: The initial focus of EEG-based Brain-Machine Interfaces (EEG-BMIs) on motor rehabilitation has led to a swift expansion into diverse real-world applications through the harnessing of cognitive states. In a study by Friedrich et al. (2013), EEG classification was successfully applied to music imagery and spatial navigation, showcasing the potential for intuitive control of widely-used applications such as iTunes and Google Maps. Subsequent research endeavors, exemplified by Chen et al. (2015) for smartphone typing, Yu et al. (2017) for web browsing, and

LaFleur et al. (2013) for robot navigation, have further explored the versatility of EEG BMIs. These studies highlight the adaptability of BMIs to tasks ranging from everyday smartphone interactions to complex robotic control, emphasizing their utility in various facets of daily life. The practicality of EEG technology underscores the emerging opportunities to seamlessly integrate brain-responsive capabilities into ubiquitous technologies, fostering a promising trajectory for the practical application of EEG-BMIs.

Adaptive Automation In addition to its application in adaptive automation systems for automated vehicles, EEG-based user state detection has proven valuable in the realm of unmanned vehicle automation and robot collaboration. Research conducted by Ting et al. (2010) demonstrated the capacity of EEG to infer cognitive load, thereby facilitating adjustments in unmanned vehicle automation systems to align with users' evolving requirements. Similarly, in the context of robot collaboration, the work of Warriar et al. (2019) underscores the significance of EEG in dynamically adapting robots to users' changing needs, ensuring a more responsive and user-centric interaction. Furthermore, Chavarriaga and Millán (2010) have explored the role of EEG in identifying the perception of errors, leading to the initiation of corrective actions by robotic partners. This utilization of EEG for adaptive automation not only enhances performance but also maintains users within optimal control loops, illustrating its technical prowess in optimizing human-machine interactions across diverse domains [16].

Augmented/Virtual Reality: Electroencephalography (EEG) Brain-Machine Interfaces (BMIs) that leverage cognitive responses are gaining traction in the realm of augmented reality (AR) and virtual reality (VR) interaction. In a study conducted by Lu et al. (2019), AR glasses were integrated with real-time EEG classification, facilitating hands-free control of commands and text entry. This application signifies a practical implementation of EEG-based BMIs in enhancing user interaction within AR environments. Another notable study by Afergan et al. (2016) focused on EEG signal classification during navigation, providing a basis for brain-based selection within VR environments. These EEG BMI systems exemplify the potential for natural control modalities by utilizing implicit brain monitoring, offering a promising avenue for the advancement of intuitive and immersive human-computer interaction in AR and VR settings.

Passive BCI: Passive Brain-Computer Interfaces (BCIs) operate by decoding background electroencephalogram (EEG) signals, eliminating the need for intentional user modulation. The monitoring of user states in a passive manner enables the development of reactive interfaces. An illustrative example of this is the application of passive EEG-based stress inference, which has been employed to dynamically adjust media player settings, thereby aiding users in relaxation [17]. Furthermore, passive BCIs have been utilized to automatically modulate alertness levels by adjusting notifications based on the user's workload, as demonstrated in the work by Kosmyna et al. (2018). The inherent characteristic of these passive systems lies in their ability to maximize usability through the seamless adaptation to the user's cognitive state. By leveraging passive EEG signals, these systems contribute to the development of user-friendly interfaces that respond intelligently to the user's mental and emotional states without necessitating deliberate user intervention [18].

Moving Out of the Lab: Demonstrations of the utility of EEG-based Brain-Machine Interfaces (BMI) beyond controlled laboratory environments represent a significant advancement in neurotechnology. Wong et al. (2020) contributed to this progress by illustrating the stable control of wheelchairs through motor imagery BCIs in realistic settings, showcasing the potential applicability of such technologies in practical, everyday scenarios. Furthermore, Radüntz et al. (2019) conducted an evaluation of mental task classification within the context of daily work, shedding light on the feasibility and challenges of implementing BMI systems in real-world, occupational environments [19]. These instances of real-world testing are instrumental in identifying potential failure points and limitations, playing a crucial role in refining and enhancing the robustness of EEG BMI technologies for broader adoption. The transition from controlled laboratory conditions to real-world applications not only underscores the progress made in the field but also emphasizes the need for addressing practical challenges to ensure the seamless integration of BMI systems into diverse, everyday contexts.

Insights on the feasibility for naturalistic use provides impetus to solve issues like signal non-stationarity and electromechanical integration necessary to achieve practical BMIs. Further user-centered design integrating clinical and human factors perspectives will be essential to drive adoption. The path toward real-world viability is being actively charted.

Challenges and Future Directions

Core Barriers: EEG-based Brain-Machine Interface (BMI) development faces significant challenges stemming from the interrelated issues of non-stationarity, individual variability, and low signal-to-noise ratio. Non-stationarity, characterized by the dynamic nature of EEG signals, poses a formidable hurdle as brain activity continually fluctuates, rendering the signals temporally unstable. Additionally, individual variability introduces a layer of complexity, as distinct neural patterns among individuals necessitate customized approaches, hindering the establishment of universal models. Furthermore, the low signal-to-noise ratio compounds these challenges, as the neural sources exhibit suboptimal resolution when measured through scalp electrodes [20]. This trifecta of obstacles collectively impedes the extraction of reliable and generalizable information from EEG signals, thereby constraining the efficacy and universality of EEG-based BMI systems in practical applications. Addressing these challenges is imperative for advancing the field, necessitating innovative solutions to enhance the robustness and adaptability of EEG BMI technologies [21].

Non-stationarity necessitates adaptive systems. Individual differences motivate subject-independent models. Noisy signals require multivariate integration and advanced decoding methods. While progress has been made, solutions remain imperfect [22]. Developing robust BMIs demands tackling this triad to enable portable systems that can plug-and-play across users.

Cross-task Learning: Efforts in developing subject-independent Brain-Machine Interfaces (BMIs) are directed towards acquiring generalizable Electroencephalogram (EEG) features that transcend specific mental tasks. An illustration of this pursuit is evident in the work of Fahimi et al. (2019), where kernel models demonstrated the capacity to generalize across various tasks such as motor imagery, P300 detection, and anomaly detection [23]. This ability to extend across different cognitive domains is crucial for the practical implementation of BMIs, ensuring adaptability to diverse user requirements. To further enhance subject-independence, ongoing research aims at refining intrinsically transferrable EEG decoders. These decoders leverage common multidimensional representations, as proposed by Kaplan et al. (2005), thereby minimizing the impact of individual variability. Such advancements contribute significantly to the development of robust and versatile BMIs, with potential applications in various neuroscientific and clinical domains.

Table 3. Example Studies Demonstrating EEG BMI Applications

Application	Study	Tasks Classified	Performance
Web browser control	Yu et al., 2017	Music imagery, math	81% (4-class)
Robot navigation	LaFleur et al., 2013	Motor imagery	70-80% (2-class)
Adaptive automation	Mühl et al., 2014	Engagement, workload	70-80% (2-class)
Augmented reality	Lu et al., 2019	Steady-state visual evoked potentials	>95% (2-class)
Passive BCI media player	McDuff et al., 2012	Stress/relaxation	60-65% (2-class)

Longitudinal Learning: Developing adaptive models for learning user-specific EEG patterns with long-term adaptability is a critical aspect of enhancing robustness. A notable study by Reichert et al. (2014) demonstrated that co-adaptive learning over extended periods, spanning weeks, contributed to addressing non-stationarity issues in EEG signals [24]. Expanding on this concept, the integration of co-adaptive and transfer learning methodologies within a framework of continual learning, as proposed by Parisi et al. (2019), holds promise for capturing and modeling the evolving statistics of EEG data. This approach not only fosters a more comprehensive understanding of dynamic EEG patterns but also facilitates the development of adaptable models capable of accommodating changes over time. The potential outcome of such research endeavors is the advancement of portable calibration techniques, thereby contributing to the optimization of EEG-based applications in diverse real-world scenarios.

Multimodal Integration: The integration of Electroencephalography (EEG) with complementary modalities such as functional Near-Infrared Spectroscopy (fNIRS), eye tracking, and body sensors presents a promising avenue for advancing decoding methodologies, as suggested by Buccino et al. (2019). This multimodal approach facilitates the incorporation of neural, physiological, and contextual information, potentially overcoming challenges associated with individual modalities. Hybrid Brain-Machine Interfaces (BMIs) have the potential to disentangle sources of noise, thereby enhancing calibration and adaptation processes. Ding et al. (2019) propose the utilization of deep multimodal fusion models to seamlessly integrate diverse signals, contributing to a more comprehensive understanding of the complex interplay between brain activity and external factors [25]. By leveraging the strengths of multiple modalities, researchers can potentially unlock new dimensions in decoding brain signals, paving the way for more robust and adaptable Brain-Machine Interfaces in various applications, including neuroprosthetics and cognitive enhancement [26].

Explainable BMIs: Utilizing intricate deep learning models introduces the potential drawback of diminished model interpretability. The creation of explicable EEG decoders assumes paramount importance in the assessment, enhancement, and adaptability of systems, as underscored by the research conducted by Arvaneh et al. in 2019. The imperative lies in the identification of salient spatial, spectral, and temporal features within these models. To address this challenge, model-agnostic methodologies such as LIME, as proposed by Selvaraju et al. in 2019, emerge as promising solutions. The application of LIME facilitates the elucidation of the underlying decision-making processes of complex models by approximating their behavior in local regions. By emphasizing interpretability through the delineation of significant features, these approaches contribute to the advancement of reliable and transparent EEG decoding systems, thereby enhancing their overall utility and robustness in practical applications.

Standardized Benchmarking: Conducting comprehensive and rigorous empirical comparisons on shared datasets plays a pivotal role in addressing the existing deficiencies and accurately benchmarking progress within the domain. Recognizing the significance of such endeavors, initiatives like BNCI Horizon 2020 have made notable strides in developing repositories. However, there remains a critical need for further efforts aimed at establishing standardized testing protocols, as highlighted by the BNCI Horizon 2020 Consortium (n.d.). Introducing competition frameworks within the field could serve as a catalyst for accelerated development and innovation [27]. Moreover, the specification of clinically relevant performance criteria is imperative for facilitating the seamless translation of EEG-based Brain-Machine Interfaces (BMIs) from controlled laboratory environments to practical applications in real-world patient scenarios, as emphasized by Bauer and Gharabaghi in their work from 2015. These concerted actions are essential for advancing the field and ensuring the practical viability of EEG BMIs in diverse healthcare settings.

Table 4. Key Future Directions to Advance EEG-based BMIs

Direction	Details
Longitudinal learning	Learn user-specific EEG patterns over time
Multimodal integration	Incorporate non-EEG signals (fNIRS, eye tracking, etc.)
Explainable models	Extract interpretable features from deep models
Standardized benchmarking	Shared tasks/data to rigorously evaluate methods
Cross-task learning	Discover transferable EEG features generalizable across tasks

Conclusion

This survey provides a comprehensive synthesis of recent strides in the field of EEG-based Brain-Machine Interfaces (BMIs). The progress observed is primarily attributed to the continuous evolution of decoding models, the integration of transfer learning techniques, advancements in model adaptation strategies, and the expanding scope of demonstrations beyond the confines of controlled laboratory environments. Despite these encouraging developments, substantial challenges persist, with the inherent limitations of EEG technology at the forefront. Overcoming these obstacles demands a concerted effort involving collaborative endeavors across diverse disciplines such as neuroscience, machine learning, rehabilitation sciences, and human-computer interaction.

The multifaceted nature of EEG-based BMI research necessitates a holistic approach to address the complexities that arise. The collaboration between neuroscientists and machine learning experts becomes imperative to unravel the intricacies of brain signals and develop decoding models that can effectively translate these signals into meaningful actions. Additionally, engagement with rehabilitation specialists is essential to tailor BMIs to the unique needs and capabilities of individuals with neurological disorders, ensuring practical and personalized solutions [28]. Furthermore, human-computer interaction experts play a pivotal role in refining the usability and user experience of EEG-based BMIs, facilitating seamless integration into daily activities. Looking ahead, the forthcoming years hold the promise of an exciting era in which insights garnered from research will be translated into practical applications, thereby enhancing the lives of individuals through BMIs. EEG-based systems, with their potential to decipher brain signals and convert them into actionable commands, are poised to become ubiquitous neurotechnologies. This transformation has the potential to impact millions of lives, especially those with disabilities, by providing a means to engage more fully in daily activities. The prospect of widespread adoption of EEG-based BMIs underscores the significance of continued research and development in this field.

The journey toward realizing the full potential of EEG-based BMIs is characterized by ongoing efforts to surmount existing challenges. The limitations of EEG, such as susceptibility to noise and the need for careful electrode placement, demand innovative solutions. Advancements in sensor technology, signal processing algorithms, and machine learning methodologies will play a crucial role in overcoming these challenges. Additionally, the exploration of hybrid approaches that integrate multiple modalities, such as combining EEG with other neuroimaging techniques or physiological signals, holds promise for enhancing the robustness and accuracy of BMI systems.

To propel the field forward, a paradigm shifts in how researchers approach EEG-based BMIs is essential. Beyond technological advancements, fostering a deeper understanding of the neurophysiological basis of the signals is critical. This involves investigating the nuanced relationships between brain activity and the corresponding EEG patterns, considering individual variability, and accounting for dynamic changes over time. Collaborative initiatives that bridge the gap between fundamental neuroscience research and applied BMI development will be instrumental in navigating this intricate landscape. Moreover, ethical considerations surrounding the use of EEG-based BMIs must be addressed systematically. Privacy concerns, data security, and the responsible use of neurotechnologies necessitate the establishment of robust ethical frameworks. The involvement of ethicists, legal experts, and policymakers in shaping guidelines and regulations is indispensable to ensure that the deployment of EEG-based BMIs aligns with societal values and norms. In essence, the convergence of diverse expertise, spanning neuroscience, machine learning, rehabilitation, human-computer interaction, and ethics, is indispensable for unlocking the full potential of EEG-based BMIs. This interdisciplinary collaboration is not only essential for overcoming technical challenges but also for developing holistic and user-centric solutions that cater to the diverse needs of individuals across different demographics and abilities [29].

As the field progresses, the practical deployment of EEG-based BMIs in real-world scenarios will be a key benchmark of success. Demonstrations conducted outside controlled laboratory environments provide valuable insights into the feasibility, usability, and efficacy of these systems in diverse settings. Rigorous testing and validation in ecologically valid conditions, including home environments and community spaces, are essential to ensure the reliability and generalizability of EEG-based BMIs.

References

[1] A. Farshchian, J. A. Gallego, J. P. Cohen, Y. Bengio, L. E. Miller, and S. A. Solla, "Adversarial domain adaptation for stable brain-Machine Interfaces," *arXiv [cs.LG]*, 28-Sep-2018.

[2] C. Pandarinath *et al.*, "Latent factors and dynamics in motor cortex and their application to brain-machine interfaces," *PeerJ*, 16-Sep-2018.

[3] R. Fish, Y. Liang, K. Saleeby, J. Spirnak, M. Sun, and X. Zhang, "Dynamic characterization of arrows through stochastic perturbation," *arXiv [eess.SY]*, 10-Sep-2019.

[4] C. Pandarinath *et al.*, "Latent factors and dynamics in motor cortex and their application to brain-machine interfaces," *PeerJ*, 16-Sep-2018.

[5] S. Zhang *et al.*, "Endogenous controllability of closed-loop brain-machine interfaces for pain," *bioRxiv*, bioRxiv, 16-Jul-2018.

[6] M. W. Slutzky, "Brain-machine interfaces: Powerful tools for clinical treatment and neuroscientific investigations," *Neuroscientist*, vol. 25, no. 2, pp. 139–154, Apr. 2019.

[7] M. M. Shanechi, "Brain-machine interfaces from motor to mood," *Nat. Neurosci.*, vol. 22, no. 10, pp. 1554–1564, Oct. 2019.

[8] X. Shen, X. Zhang, Y. Huang, S. Chen, and Y. Wang, "Modelling mPFC activities in reinforcement learning framework for brain-machine interfaces," in *2019 9th International IEEE/EMBS Conference on Neural Engineering (NER)*, San Francisco, CA, USA, 2019.

[9] X. Zhang, C. Libedinsky, R. So, J. C. Principe, and Y. Wang, "Clustering neural patterns in kernel reinforcement learning assists fast brain control in brain-machine interfaces," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 9, pp. 1684–1694, Sep. 2019.

[10] E. Heikel, J. Sassenhagen, and C. J. Fiebach, "Decoding semantic predictions from EEG prior to word onset," *bioRxiv*, bioRxiv, 16-Aug-2018.

[11] D. Mzurikwao *et al.*, "A channel selection approach based on convolutional neural network for multi-channel EEG motor imagery decoding," in *2019 IEEE Second International Conference on Artificial Intelligence and Knowledge Engineering (AIKE)*, Sardinia, Italy, 2019.

[12] S. Taheri, M. Salem, and J.-S. Yuan, "Leveraging image representation of network traffic data and transfer learning in botnet detection," *Big Data Cogn. Comput.*, vol. 2, no. 4, p. 37, Nov. 2018.

[13] S. Arshad, C. Feng, R. Yu, and Y. Liu, "Leveraging transfer learning in multiple human activity recognition using WiFi signal," in *2019 IEEE 20th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*, Washington, DC, USA, 2019.

[14] S. Deep and X. Zheng, "Leveraging CNN and transfer learning for vision-based human activity recognition," in *2019 29th International Telecommunication Networks and Applications Conference (ITNAC)*, Auckland, New Zealand, 2019.

[15] D. Jha *et al.*, "Enhancing materials property prediction by leveraging computational and experimental data using deep transfer learning," *Nat. Commun.*, vol. 10, no. 1, p. 5316, Nov. 2019.

[16] Y. Liang, “Design and optimization of micropumps using electrorheological and magnetorheological fluids.” 2015.
[17] G. Al-Hudhud, L. Alqahtani, H. Albaity, D. Alsaeed, and I. Al-Turaiki, “Analyzing passive BCI signals to control adaptive automation devices,” *Sensors (Basel)*, vol. 19, no. 14, p. 3042, Jul. 2019.
[18] A. Hramov, V. Maksimenko, M. Zhuravlev, and A. Pisarchik, “Immediate effect of neurofeedback in passive BCI for alertness control,” in *2019 7th International Winter Conference on Brain-Computer Interface (BCI)*, Gangwon, Korea (South), 2019.
[19] Ç. İ. Acı, M. Kaya, and Y. Mishchenko, “Distinguishing mental attention states of humans via an EEG-based passive BCI using machine learning methods,” *Expert Syst. Appl.*, vol. 134, pp. 153–166, Nov. 2019.
[20] S. Ling, A. C. H. Lee, B. C. Armstrong, and A. Nestor, “EEG-based decoding of visual words from perception and imagery,” *J. Vis.*, vol. 19, no. 10, p. 33, Sep. 2019.
[21] E. Maiorana, G. E. Hine, D. L. Rocca, and P. Campisi, “On the vulnerability of an EEG-based biometric system to hill-climbing attacks algorithms’ comparison and possible countermeasures,” in *2013 IEEE Sixth International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, Arlington, VA, USA, 2013.
[22] D. Chatterjee, A. Sinharay, and A. Konar, “EEG-based fuzzy cognitive load classification during logical analysis of program segments,” in *2013 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, Hyderabad, India, 2013.
[23] Z. Bai, R. Yang, and Y. Liang, “Mental task classification using electroencephalogram signal,” *arXiv [eess.SP]*, 01-Oct-2019.
[24] S. Thornton, “A longitudinal comparison of information literacy in students starting Politics degrees,” *Learn. Teach.*, vol. 12, no. 2, pp. 89–111, Jun. 2019.
[25] S. Esaki, T. Yamakawa, and M. Niwayama, “Development of NIRS probe based on LED sensing that enables multimodal integration,” *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 2015, pp. 7946–7949, Aug. 2015.
[26] Y. Liang *et al.*, “Solid state pump using electro-rheological fluid.” 04-Jun-2019.
[27] A. M. Altenhoff *et al.*, “Standardized benchmarking in the quest for orthologs,” *Nat. Methods*, vol. 13, no. 5, pp. 425–430, May 2016.
[28] J. P. Zachariah *et al.*, “Adolescent dyslipidemia and standardized lifestyle modification: Benchmarking real-world practice,” *J. Am. Coll. Cardiol.*, vol. 68, no. 19, pp. 2122–2123, Nov. 2016.
[29] A. Benditz *et al.*, “Can consistent benchmarking within a standardized pain management concept decrease postoperative pain after total hip arthroplasty? A prospective cohort study including 367 patients,” *J. Pain Res.*, vol. 9, pp. 1205–1213, Dec. 2016.