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Title: Emerging EEG-BCI Approaches in Rehabilitation: A Narrative Review

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Abstract

Noninvasive electroencephalography (EEG)-based brain–computer interfaces (BCIs) have emerged as promising tools for restoring motor and communication functions in individuals with neurological impairments. Despite substantial technological progress, the translation of EEG-based BCI systems from laboratory environments to routine clinical rehabilitation remains limited. This critical narrative review synthesizes advances reported between 2021 and 2025, focusing on endogenous paradigms such as motor imagery and exogenous paradigms including P300 and steady-state visually evoked potentials (SSVEP), as well as developments in signal processing, machine learning, and rehabilitation applications. Relevant peer-reviewed studies were identified through IEEE Xplore, PubMed, and Scopus and evaluated through a thematic synthesis approach. Owing to considerable methodological heterogeneity across paradigms, hardware configurations, and outcome measures, a formal meta-analysis was not performed. Instead, studies were critically examined in terms of acquisition hardware, feature extraction and classification strategies, and clinical rehabilitation applications. The reviewed literature indicates that EEG-based BCIs can achieve high classification accuracies under controlled conditions, ranging from 93.2% for motor imagery systems to over 99% for P300-based spellers. Recent self-supervised and transformer-based approaches have further improved cross-subject generalization and reduced calibration requirements, reporting accuracies of approximately 94–95%. However, real-world deployment continues to be constrained by signal instability, motion artifacts, limitations of low channel wearable devices, and a lack of longitudinal evidence demonstrating functional outcomes and usability. Future research should prioritize robustness, adaptability, and long-term clinical reliability through standardized real world validation, user-centered design, and interdisciplinary collaboration to facilitate the transition of EEG-based BCIs into scalable rehabilitation technologies.

Keywords: Brain-Computer Interface (BCI); Electroencephalography (EEG); Motor Imagery; Deep Learning; Neurorehabilitation; Clinical Translation

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Highlights:

- BCI classification performance is highly dependent on the chosen neural paradigm, feature extraction strategy, and validation protocol.
- Deep learning architectures show strong potential for automated EEG feature extraction, though their reported accuracy varies significantly with dataset and evaluation conditions.
- Self-supervised learning approaches effectively reduce subject-specific calibration time and enhance cross-subject generalization.
- Paradigm selection involves key trade-offs: SSVEP offers high speed but requires visual stimulation; P300 enables reliable communication but demands sustained attention; motor imagery provides stimulus-free control but faces higher inter-subject variability.

Plain Language Summary:

Brain-computer interfaces (BCIs) use EEG headsets to detect neural activity, enabling individuals with movement or speech impairments to control devices such as computers or robotic arms using thought alone. This review synthesizes current research on noninvasive, EEG-based BCIs applied to neurorehabilitation. While laboratory studies report high performance—exceeding 99% accuracy for some communication systems and around 95% for virtual reality therapy—real-world application remains challenging. Emerging artificial intelligence methods are improving system adaptability and reducing the need for lengthy user training. However, outside controlled environments, several barriers persist: a significant subset of users, particularly older adults or stroke survivors, struggle to generate consistent neural patterns; consumer-grade headsets with fewer sensors often capture lower-quality data; and motion artifacts frequently disrupt signal clarity. Additionally, ethical concerns regarding neural data privacy and equitable access have yet to be fully addressed. Effective BCI design must match both the user's capabilities and the intended task; for instance, visual flicker-based systems suit users with intact vision, whereas motor imagery approaches are better suited for post-stroke motor retraining. To become practical clinical tools, future BCI systems require validation in real-world settings, user-centered design, and integration with established rehabilitation therapies.

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Introduction

A Brain Computer Interface (BCI) establishes a direct communication channel between the brain and external devices translating neural activity into actionable commands without requiring physical movement(Borikar et al., 2014). At its core, BCI decodes electrical patterns generated by synchronized neuronal firing in the cerebral cortex, converting raw biosignals into control outputs for machines, prosthetics, or software interfaces(Fuentes-Aguilar et al., 2022).

While signal acquisition in BCI systems can be categorized into invasive, semi invasive, and noninvasive approaches(Rao, 2013), practical considerations have made non-invasive electroencephalography (EEG) the dominant platform for both research and clinical deployment. Invasive methods, although offering high signal fidelity, involve significant surgical risks and biocompatibility issues, limiting their use to acute cases(Ortiz-Rosario & Adeli, 2013). In contrast, EEG provides a safe, portable, and cost-effective alternative by capturing voltage fluctuations via scalp electrodes(Jahankhani & Revett, 2006; Värbu et al., 2022).This accessibility has established EEG as the standard for longitudinal studies and real world rehabilitation applications, despite the inherent challenges of signal noise.

Yet EEG's noninvasive nature comes at a cost: signals are inherently noisy, contaminated by artifacts from eye movement, muscle activity, and environmental interference (e.g., 50/60 Hz line noise). Effective BCI operation therefore hinges on robust signal processing pipelines, typically comprising preprocessing, feature extraction, and classification(Vishwakarma et al., 2020) .Among neural oscillations, beta-band activity (13–30 Hz) has drawn particular attention in motor related BCIs due to its strong modulation during movement preparation and execution.

One of the most impactful applications of BCI lies in neurorehabilitation. For individuals with stroke, spinal cord injury, Parkinson's disease, or Amyotrophic Lateral Sclerosis (ALS), BCIs can

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restore lost motor function, reestablish communication, or even modulate chronic pain by targeting maladaptive neural circuits .In prosthetic control, BCIs allow users to operate artificial limbs through imagined movement, significantly enhancing independence (Angulo Medina Et Al., 2024; Danesh Et Al., 2025; Grigore & Ali). BCI systems have also shown promise in pain reduction by altering neural activity to decrease sensitivity to painful stimuli(Demarest et al., 2024).

The field has evolved rapidly through a series of methodologically diverse and technically influential studies. Guger et al.(Guger et al., 2001) demonstrated that imagined hand movements could be classified with 70–95% accuracy using only two EEG channels, enabling internet based device control and proving that minimal hardware setups could support functional BCI systems. Müller-Putz et al.(Müller-Putz et al., 2005) integrated BCI with functional electrical stimulation to restore hand function in paralyzed patients, marking a pivotal step toward closed loop neurorehabilitation. Kamousi et al.(Kamousi et al., 2005) achieved 80% accuracy in four class motor imagery classification for prosthetic control, reinforcing the potential of endogenous signals for dexterous tasks. More recently, Li et al.(Li et al., 2022) employed a combined Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) architecture for joint feature extraction and classification, using a fully connected layer in the final stage to reach 87.68% accuracy. Abdulwahab et al.(Abdulwahab, 2021) developed a motor imagery BCI system that applied a Chebyshev filter for preprocessing and maximum overlap discrete wavelet transform (MODWT) to extract theta and delta band features, achieving 97.36% accuracy in four class classification with a cubic Support Vector Machines (SVM). Parallel to these advances, hybrid strategies that fuse EEG with electromyography (EMG) have emerged to enhance system robustness and reduce false positives by leveraging complementary physiological signals (Danesh et.al 2026).

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Despite remarkable progress in algorithmic sophistication and laboratory-scale validation, a persistent gap separates EEG-based BCI research from routine clinical adoption. Many systems demonstrate high classification accuracy only under tightly controlled conditions, require extensive subject-specific calibration, or rely on hardware that is impractical for home-based rehabilitation.

This review confronts these limitations by critically examining recent EEG-based BCI studies in rehabilitation not as a passive inventory of accuracies, but as a structured analysis of how specific methodological choices in signal acquisition, feature representation, and classification shape system robustness, usability, and clinical relevance. We aim to identify not merely what works, but why it works, under what constraints, and for which patient populations thereby offering engineers and clinicians an evidence-based foundation for designing BCI systems that function effectively in real world settings, not just in controlled experiments.

Methods

This critical narrative review synthesizes methodological and clinical advances in EEG-based BCI systems for neurorehabilitation reported between January 2021 and March 2025. Literature searches were conducted in IEEE Xplore, PubMed, and Scopus using the Boolean query: ("EEG" OR "electroencephalography") AND ("brain-computer interface" OR "BCI") AND ("rehabilitation" OR "neurorehabilitation" OR "prosthetic control" OR "stroke") AND ("deep learning" OR "machine learning" OR "signal processing"). Supplementary searches in Frontiers and MDPI captured recent interdisciplinary contributions.

Records were screened by title and abstract, followed by full-text assessment against predefined criteria. Inclusion required: (1) peer-reviewed English-language studies; (2) use of non-invasive

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EEG for rehabilitation-oriented applications; and (3) reporting of quantitative performance metrics or qualitative usability/clinical outcomes. Exclusion criteria encompassed invasive/semi-invasive approaches, studies exclusively involving healthy volunteers without rehabilitation implications, and articles lacking sufficient methodological detail. The final synthesis comprised 61 studies.

Given substantial heterogeneity in BCI paradigms, hardware configurations, preprocessing pipelines, and validation protocols, quantitative meta-analysis was inappropriate. Instead, a narrative thematic synthesis was performed across three domains: (i) signal acquisition hardware, (ii) feature extraction and classification methodologies, and (iii) rehabilitation applications and functional outcomes. Methodological quality was assessed qualitatively by critically appraising experimental design, validation rigor (intra- vs. cross-subject), and reporting transparency, rather than through formal risk-of-bias scoring. Technical performance metrics (e.g., accuracy, ITR) were explicitly distinguished from clinically meaningful rehabilitation outcomes to prevent overinterpretation of laboratory results. Older foundational references were retained solely to establish core neurophysiological concepts and BCI terminology, clearly distinguished from the primary 2021–2025 search window.

Figure 1 illustrates the conceptual workflow guiding study identification, thematic organization, and synthesis. This structured narrative approach aligns with best practices for rapidly evolving technical fields where standardized clinical trials remain limited.

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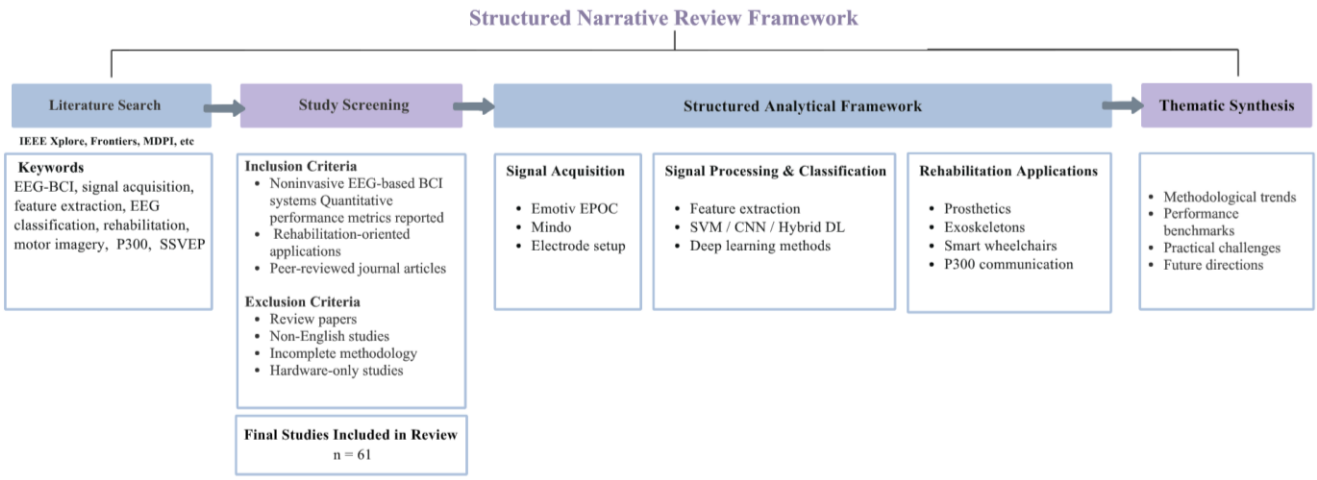


Figure (1): Structured narrative review framework

Analytical Framework for Thematic Synthesis

To enable structured comparison across methodologically heterogeneous studies, we adopted the canonical EEG-BCI pipeline as an organizing framework. This pipeline comprising signal acquisition, preprocessing, feature extraction, and classification served as a scaffold for extracting and synthesizing methodological details from each reviewed article. Specifically, we examined: (i) hardware specifications and electrode configurations under acquisition; (ii) artifact suppression strategies and feature representation choices under preprocessing; and (iii) model architectures and validation protocols under classification. This framework allowed us to systematically assess how technical decisions at each stage influence reported performance and clinical applicability. Figure 2 illustrates this analytical scaffold.

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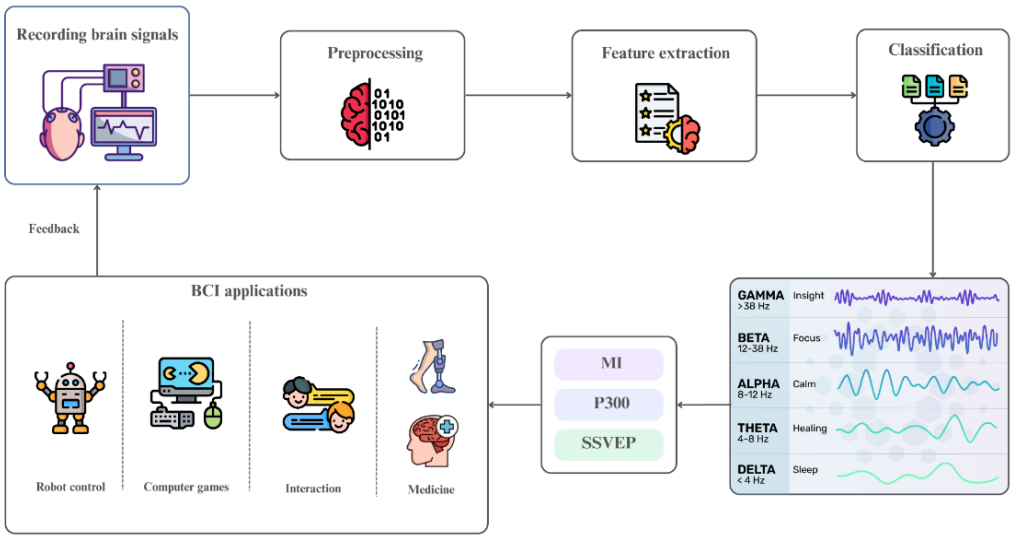


Figure (2) Different Components of a BCI System

1- Signal Acquisition

Among the reviewed studies, noninvasive EEG-based acquisition methods were overwhelmingly preferred for rehabilitation-oriented BCI applications due to their safety, portability, and suitability for long-term use. Although invasive and semi invasive techniques can provide higher signal quality and spatial resolution, their clinical risks and limited practicality restrict their widespread adoption in rehabilitation settings(Bjånes et al., 2024; Guger et al., 2018). Figure 3 illustrates the electrode placement configurations for intracortical microelectrodes (invasive), electrocorticography (semi-invasive), and scalp EEG (noninvasive).

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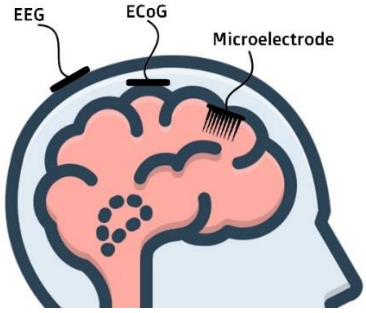


Figure (3): Electrode placement configurations across invasive, semi-invasive, and noninvasive EEG acquisition methods.

The reviewed studies demonstrated a clear preference for commercially available, low-channel EEG headsets in rehabilitation-oriented research. Devices such as the Emotiv EPOC frequently employed for SSVEP paradigms (Asanza et al., 2021) and the MINDO headband utilized for its dry electrode(), mobile-friendly design (Lin et al., 2014) were selected primarily for their portability and cost-effectiveness. However, this trend introduces methodological tradeoffs: while such devices enhance ecological validity, their limited spatial resolution (typically 14–16 channels) may compromise signal quality under motion artifacts or high-impedance conditions. Notably, only three of the 61 reviewed studies explicitly reported impedance values or signal to noise ratios a reporting gap that limits reproducibility.

and cross-study comparison.

The reviewed literature also demonstrated clear preferences regarding EEG paradigms used in rehabilitation applications. SSVEP-based systems were frequently adopted in studies requiring fast and reliable real-time control, particularly in assistive navigation and device interaction tasks(İşcan & Nikulin, 2018). In contrast, P300 paradigms were predominantly associated with communication-oriented applications such as spelling and selection systems, where cognitive

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attention responses could be effectively translated into commands(Picton, 1992). Motor imagery (MI) remained one of the most extensively used paradigms in motor rehabilitation studies, especially for controlling prosthetic limbs, robotic devices, and exoskeleton systems(Lotze & Cohen, 2006). Across the reviewed studies, the selection of EEG paradigms was strongly influenced by the intended rehabilitation objective, required control speed, and system complexity.

2- Signal Preprocessing & Classification

Recent advances in BCI research have increasingly shifted from traditional handcrafted feature engineering toward end-to-end deep learning architectures, driven by the need to manage high-dimensional, non-stationary neural signals under real-world noise conditions. Figure 4 presents an overview of common EEG signal processing approaches evaluated across the reviewed literature.

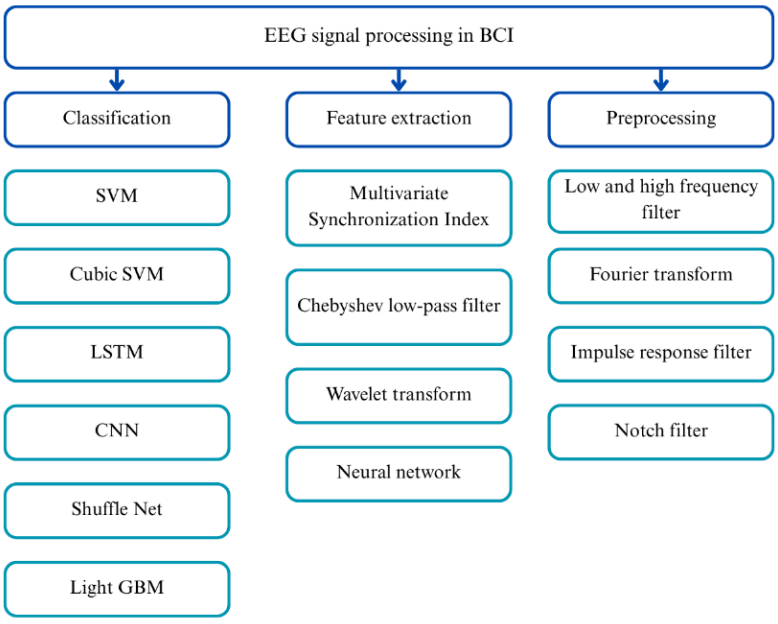


Figure (4): Schematic overview of EEG signal processing pipelines in BCI systems.

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Feature extraction remains a critical stage in EEG analysis, as it transforms preprocessed signals into informative representations that reflect task-related neural dynamics. Traditional approaches typically isolate discriminative patterns across time, frequency, time–frequency, and spatial domains (Torres et al., 2020). While time-domain metrics (e.g., variance, skewness) and spatial filtering techniques like Independent Component Analysis (ICA) effectively characterize temporal properties and suppress artifacts, their performance heavily depends on expert tuning. Frequency-domain methods, including Fast Fourier Transform (FFT) and autoregressive modeling, quantify oscillatory power across delta to gamma bands, which are strongly linked to cognitive and motor states. However, because EEG is inherently nonstationary, time–frequency techniques such as wavelet transforms and packet decompositions are often preferred for capturing transient neural events. For instance, Yin et al.(Yin et al., 2024) demonstrated that a multivariate synchronization index could decode SSVEP targets without extensive training data, significantly reducing computational overhead while preserving spectral fidelity.

Classification algorithms subsequently map extracted features to executable control commands. In BCI systems, this involves detecting paradigm-specific responses such as P300 potentials, SSVEP harmonics, or motor imagery modulations within defined epochs. These responses are typically elicited through structured external stimuli (e.g., flashing matrices for P300, flickering frequencies for SSVEP, or kinesthetic imagination for motor tasks). Classification models are broadly categorized into generative and discriminative families. Generative approaches model class-conditional probability distributions, whereas discriminative models directly optimize decision boundaries. While k-nearest neighbors (kNN) exhibit robustness to minor signal fluctuations, Support Vector Machines (SVMs) and neural networks generally achieve higher discriminative

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capacity at the cost of increased sensitivity to training-data variability and hyperparameter tuning(Guttmann-Flury et al., 2023).

Deep learning architectures have increasingly dominated this landscape by automatically learning hierarchical spatiotemporal representations from raw or minimally processed EEG, thereby reducing reliance on manual feature engineering. Convolutional Neural Networks (CNNs) excel at extracting localized spatial–spectral filters, while Long Short-Term Memory (LSTM) networks capture sequential temporal dependencies across trials. The demonstrated efficacy of these architectures in handling high-dimensional, noisy biomedical data has been well-documented across multiple modalities, including neuroimaging and electrophysiology(Danesh & Ghasemi, 2025), This cross-domain success has directly motivated their integration into EEG-based BCI pipelines, where they consistently outperform classical classifiers in controlled settings. For example, Jia et al.(Jia et al., 2023) proposed a hybrid framework combining spectral temporal CNNs, Efficient Channel Attention (ECA) modules, and LightGBM, achieving 86% peak accuracy under intra-subject cross-validation. Similarly, Sadiq et al.(Sadiq et al., 2022) everaged pretrained CNN architectures on the BCI Competition III dataset, with ShuffleNet reaching 99.52% accuracy. The authors attributed this performance to the model's ability to preserve the intrinsic time frequency structure of EEG, thereby bypassing manual feature engineering.

Recent advances in P300 speller BCIs have further addressed calibration bottlenecks through self-supervised learning. Hong et al.(Hong et al., 2025) introduced SpellerSSL, which integrates self-supervised pretraining with P300 aggregation to mitigate low signal to noise ratios and reduce calibration demands. Using a customized one-dimensional U-Net pretrained on cross-domain and in-domain EEG datasets, the system achieved 94%-character recognition with only seven stimulus

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repetitions, cutting calibration data requirements by approximately 60%. These results highlight the potential of self-supervised frameworks to enhance real-world BCI usability.

Transformer-based architectures have also shown promise in addressing cross subject variability in motor imagery classification. Liao et al.(Liao et al., 2025) proposed EEGEncoder, which couples modified transformers with Temporal Convolutional Networks (TCNs) via a Dual Stream Temporal Spatial Block (DSTS) to capture long-range spatiotemporal dependencies. Evaluated on the BCI Competition IV-2a dataset, the model achieved 74.48% subject-independent accuracy, indicating superior generalization compared to conventional deep learning approaches. Such findings underscore the growing role of attention mechanisms in developing adaptive BCI systems with reduced subject-specific calibration burdens.

The selection of an appropriate feature extraction and classification strategy must therefore balance computational complexity, validation rigor, and clinical feasibility. Algorithmic performance is highly contingent on dataset characteristics, signal quality, and evaluation protocol rather than model depth alone. Table 1 summarizes representative studies, highlighting paradigm, methodological approach, validation protocol, and reported performance.

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Table (1): Representative studies on EEG-based signal classification: methodological characteristics and validation protocols.

Authors	Brain Signal Paradigm	Feature Extraction Method	Classification Method	Accuracy
Cho et al. (Cho et al., 2021)	Motor Imagery	Bi-LSTM	Bi-LSTM	68%
Hong et al. (Hong et al., 2025)	P300	Self-supervised learning (1D U-Net)	self-supervised learning-1D UNet	94%
Liao et al. (Liao et al., 2025)	Motor Imagery	Transformers with TCN	transformers with TCN	74.48%
Bousseta et al. (Bousseta et al., 2018)	Motor Imagery	PCA and FFT	SVM	85.45%
Ghumman et al. (Ghumman et al., 2021)	---	Filter Bank CSP (FBCSP)	SVM	67.95%
Hameed et al. (Hameed et al., 2024)	Motor Imagery	Self-attention process	Transformer	BCI IV-2a = 88.75% BCI IV-2b = 84.20%
Huang et al. (Huang et al., 2022)	Motor Imagery	CNN	CNN	92%

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Jia et al.(Jia et al., 2023)	Motor Imagery	Efficient Channel Attention	LIGHT GBM	86%
Liu et al. (Liu et al., 2024)	Motor Imagery	EEG MoE-Prob-Transformer (EMPT)	Transformer	95.24%
Sadiq et al. (Sadiq et al., 2022)	Motor Imagery	Continuous Wavelet Transform	CNN (ShuffleNet)	99.52%

It should be noted that the accuracies reported in Table 1 reflect heterogeneous experimental conditions, including different datasets, preprocessing pipelines, and evaluation protocols. Direct numerical comparison across studies is therefore methodologically limited. The primary value of this synthesis lies in identifying methodological trends such as the shift toward self-supervised and transformer-based architectures rather than ranking algorithms by peak accuracy alone. The variation in reported performance cannot be attributed solely to algorithmic sophistication. For instance, the 99.52% accuracy reported by Sadiq et al.(Sadiq et al., 2022) using a pretrained ShuffleNet highlights how benchmark-optimized models can achieve exceptional scores under controlled settings, though such results require careful interpretation regarding cross-subject generalizability and potential overfitting. Conversely, the 68% accuracy observed in Cho et al.(Cho et al., 2021) with a Bi-LSTM model reflects the inherent challenges of inter trial variability and non-stationary neural dynamics in more complex evaluation contexts. Similarly, the robust performance of SVM in Abdulwahab et al.(Abdulwahab, 2021) (97.36%) demonstrates that classical algorithms, when paired with well-engineered features like MODWT coefficients, remain highly competitive. This evidence confirms that algorithm selection must align with signal

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representation quality and validation rigor, rather than adhering to a deeper-is-better assumption. Future reporting should therefore prioritize transparency in dataset characteristics and cross-subject generalization metrics to accelerate the translation of BCI systems from laboratory prototypes to reliable clinical tools.

3-Applications of EEG-Based BCI in Rehabilitation

The reviewed studies demonstrated that EEG based BCI systems have been increasingly applied across clinical rehabilitation contexts and assistive/interactive environments, with a predominant focus on restoring motor and communication function. In the medical field, most studies focused on motor rehabilitation, speech rehabilitation, pain management, and the mitigation of neurological disorders, whereas non-medical applications primarily involved robotic control and brain-computer interaction in virtual environments and gaming systems. Figure (5) summarizes the major application domains identified in the reviewed literature.

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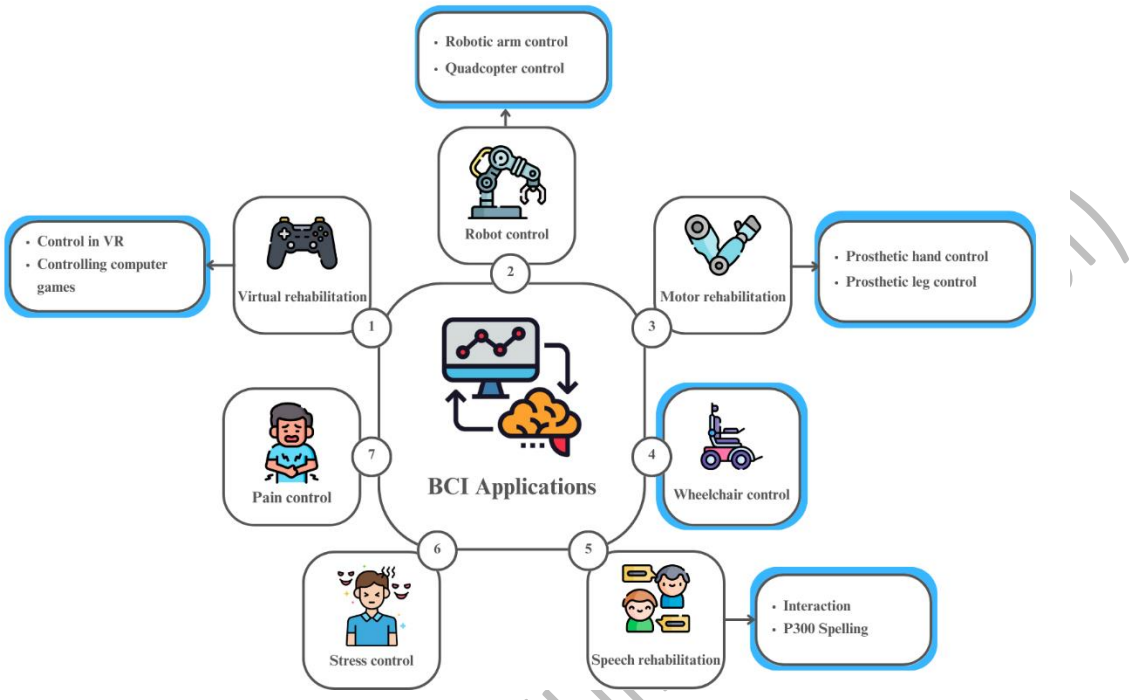


Figure (5): Thematic distribution of rehabilitation-oriented BCI applications identified in the reviewed literature

Virtual rehabilitation emerged as one of the most actively explored research areas, particularly due to the integration of BCI systems with virtual reality (VR) platforms. Several studies implemented rehabilitation protocols in simulated environments prior to real-world deployment, enabling safer and more flexible system evaluation. One of the earliest demonstrations was reported by Leeb and colleagues (Leeb et al., 2007), who showed that a completely paralyzed patient could control a virtual wheelchair using a motor imagery (MI)-based BCI system within a VR environment. More recent studies combined VR, robotics, and BCI technologies to enhance rehabilitation outcomes. For example, Zhang et al. (Zhang et al., 2015) proposed a lower-limb rehabilitation system integrating robotic assistance with VR-based motor training, allowing users to perform multiple

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movement-related commands such as turning and acceleration. The simultaneous interaction between robotic feedback and virtual motor representation was reported to improve rehabilitation performance.

The reviewed studies also indicated increasing interest in combining neurofeedback mechanisms with gaming environments. In particular, BCI controlled computer games were frequently utilized for cognitive rehabilitation and attention training. Amin et al.(Amin et al., 2022) developed a neurofeedback-based gaming system for attention deficit treatment using EEG signals acquired through the Neurosky sensor. Signal classification was performed using SVM, LSTM, and kNN algorithms, achieving a reported classification accuracy of 89%. These findings suggest that gamified BCI environments may improve user engagement while simultaneously supporting rehabilitation-oriented neurofeedback training.

Beyond gamified environments, BCI systems have also been extensively explored for direct robotic control in rehabilitation contexts.

Robotic control represented another major application domain identified across the reviewed studies. Several investigations employed MI-based BCI systems for controlling robotic arms and assistive devices without physical interaction. Xu et al.(Xu et al., 2020) demonstrated remote robotic arm control using imagined movements transmitted through a wireless communication framework. In addition to motor control, tactile feedback from the robotic gripper was converted into sensory feedback commands, improving interaction performance. The reported success rates for the evaluated tasks reached 66.2 ± 6% and 78 ± 6.1%, respectively(Xu et al., 2020). Other studies adopted SSVEP-based paradigms for robotic control applications. In study (Zhang et al., 2023) , a stimulus brightness modulation strategy was introduced to increase the number of control commands available in VR-SSVEP systems for stroke rehabilitation applications. Compared with

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MI paradigms, SSVEP-based systems generally demonstrated advantages including higher information transfer rates, simpler usability, and shorter training requirements (KONGLW & Chen, 2015). However, prolonged exposure to flickering visual stimulation remained a significant limitation, particularly for patients with neurological disorders who may experience discomfort during extended use.

Motor rehabilitation and prosthetic control constituted one of the most extensively investigated BCI application areas. Across multiple studies, imagined motor activity was successfully translated into prosthetic or exoskeleton control commands, supporting both functional assistance and neural plasticity enhancement (Wen et al., 2021). Kim and colleagues(Kim et al., 2021) utilized the EMOTIV EPOC headset together with a genetic algorithm-based processing framework to classify four imagined upper-limb movement states, achieving a reported accuracy of 93.2%. The findings suggested the feasibility of applying low-cost EEG systems for prosthetic control in rehabilitation settings. Similarly, Jochumsen et al. (Jochumsen et al., 2021) developed a BCI-controlled wrist exoskeleton fabricated using 3D printing technology for stroke rehabilitation. Imagined hand extension extracted from EEG signals was used to control the exoskeleton, resulting in a true positive rate of 86 ± 12% across healthy participants. These studies collectively highlighted the growing feasibility of combining wearable EEG systems with low-cost robotic rehabilitation technologies. Figure (6) illustrates representative BCI-based control mechanisms for wheelchairs and prosthetic devices. While motor restoration has dominated the literature, a parallel body of work has focused on communication rehabilitation through BCI-mediated spelling and selection systems.

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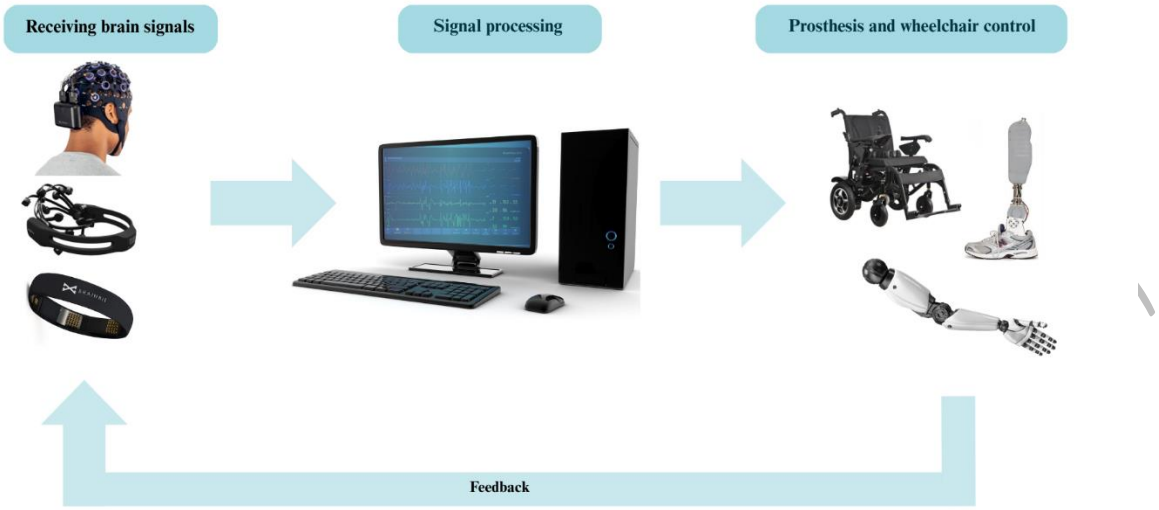


Figure (6): Schematic representation of BCI-driven control mechanisms for prosthetic limbs and exoskeletons in motor rehabilitation studies.

Speech rehabilitation was another prominent application area identified in the reviewed literature, with most studies relying on P300-based spelling and communication systems. Rather than focusing solely on conventional two-dimensional interfaces, recent investigations emphasized improving user comfort, classification performance, and immersive interaction through three-dimensional paradigms and VR integration. Qu et al. (Qu et al., 2018) demonstrated that replacing traditional 2D visual stimuli with 3D cube-based paradigms enhanced P300 response effectiveness and improved user comfort. Similarly, Huang et al. (Huang, 2019) reported that VR-integrated 3D interfaces achieved superior performance compared with conventional 2D speech rehabilitation systems. Nourzadeh et al. (Noorzadeh et al., 2020) further proposed an expanded 3D P300 paradigm designed to improve symbol representation across rows, columns, and depth dimensions while reducing visual fatigue. Comparative analysis between conventional 2D and extended 3D paradigms confirmed improvements in classification performance and usability. Table (2) summarizes the performance metrics and outcomes reported in the reviewed rehabilitation-

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oriented BCI studies. Reported accuracy values reflect study-specific technical performance and must be contextualized within each study's experimental design rather than treated as universal benchmarks of clinical efficacy. Differences in datasets, participant populations, BCI paradigms, preprocessing methods, and validation protocols should be considered when interpreting these values.

Table (2): Reviewed Articles in BCI Rehabilitation

Authors	Application Area	Brain Paradigm	Task	Success Rate
Leeb et al.(Leeb et al., 2007)	Virtual Rehabilitation	Beta Oscillations	Command "Go" from one virtual avatar to another	90%
Ortner et al.(Ortner et al., 2012)	Virtual Rehabilitation	Motor Imagery	Imagining hand movements in VR	90.4%
Lupu et al.(Lupu et al., 2018)	Virtual Rehabilitation	Motor Imagery	Controlling virtual characters in VR	85.44%
Zhang et al.(Zhang et al., 2015)	Virtual-Rehabilitation Robotics	SSMVEP	Moving a virtual person in four directions: backward, forward, left, and right	ACC: 85.6±10.1% ITR(bits/min): 10.72±4.82

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Wang et al.(Wang et al., 2023)	Virtual Rehabilitation	SSVEP	Controlling 16 movements in VR	95%
Li et al.(Li et al., 2021)	Virtual Rehabilitation	P300	Playing and controlling the MindGomoku game	90.7%
Amin et al. (Amin et al., 2022)	Virtual Rehabilitation	---	Shooting or not shooting at a target in therapeutic games for attention deficit treatment	89%
Xu et al. (Xu et al., 2020)	Robotics	Motor Imagery	Two tasks of imagining hand movements to grasp an object using a robotic arm	66.2±6% 78±6.1%
Kapgate et al. (Kapgate, 2022)	Robotics	SSVEP & P300	Flight control in a quadcopter: combining two types of brain potentials SSVEP and P300	Not reported
Kim et al. (Kim et al., 2021)	Motor Rehabilitation	Motor Imagery	Flexion and extension of the arm and hand	92.3%
Jochumsen et al. (Jochumsen et al., 2021)	Motor Rehabilitation	Motor Imagery	Inducing neural plasticity with a three-	86±12%

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			dimensional exoskeleton for the wrist	
Ma et al. (Ma et al., 2024)	Motor Rehabilitation	Motor Imagery	Four tasks: grasping with the left hand, grasping with the right hand, imagining grasping with the left hand, and imagining grasping with the right hand.	r = 0.399, P < 0.05
Nama et al. (Nama & Samanta, 2024)	Motor Rehabilitation	Motor Imagery	Two control commands on 36 target symbols	2.9% mean error:
Guo et al. (Guo et al., 2022)	Motor Rehabilitation	SSVEP	Hand function rehabilitation after stroke: Fugl-Meyer Assessment for Upper Extremity (FMA-UL), Wolf Motor Function Test (WMFT), and Modified Ashworth Scale (MAS)	full score: 10.05 ± 8.03, p = 0.001

Huang et al. (Huang, 2019)	Speech Rehabilitation	P300	Activation of the blinking button in the stereoscopic environment	96%
Qu et al. (Qu et al., 2018)	Speech Rehabilitation	P300	Activation of the blinking button in the stereoscopic environment	Not reported
Norzadeh et al.(Noorzadeh et al., 2020)	Speech Rehabilitation	P300	Activation of the blinking button for the Stereoscopic	73.25% - 74.65%
Korkmaz et al.(Korkmaz et al., 2022)	Speech Rehabilitation	P300	15 Blinks	99.81%
Fouad et al.(Fouad, 2021)	Speech Rehabilitation	P300	Blinking of Row Columns	90%

Note: Success rates and performance metrics are reported as originally defined by each study. Values include classification accuracy, information transfer rate (ITR), clinical scale scores, or correlation coefficients, reflecting heterogeneous evaluation frameworks. Direct cross-study comparison is therefore methodologically constrained.

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Results

The reviewed literature demonstrated that classification performance in EEG-based BCI systems is strongly influenced by the selected neural paradigm, feature extraction strategy, and classification architecture. Earlier rehabilitation-oriented systems generally relied on conventional signal processing and machine learning approaches, achieving moderate-to-high performance under controlled experimental conditions. For instance, an earlier foundational study by Leeb and colleagues(Leeb et al., 2007) reported an accuracy of 90% in a wheelchair control application using beta oscillations. More recent studies have also reported high classification accuracies using advanced signal-processing and machine-learning or deep-learning approaches. Abdulwahab and colleagues(Abdulwahab, 2021) achieved an accuracy of 97.36% using a cubic SVM classifier with MODWT-based feature extraction, while Sadiq and colleagues(Sadiq et al., 2022) reached an accuracy of 99.52% by employing a pretrained ShuffleNet architecture. These values represent study-specific technical performance and must be interpreted within their respective experimental contexts. High classification accuracy under controlled, intra-subject validation does not equate to clinical effectiveness or functional rehabilitation benefit. Accordingly, technical metrics are reported separately from clinically meaningful outcomes (e.g., motor recovery scales, usability scores) to avoid conflating algorithmic benchmark performance with patient-centered therapeutic impact. Table 1 summarizes representative studies employing LSTM, SVM, and CNN-based classifiers across different paradigms. While CNN-based approaches frequently report high accuracies in intra-subject validation settings, direct numerical ranking across algorithms is methodologically limited due to heterogeneity in datasets, preprocessing pipelines, participant populations, and evaluation protocols. The observed performance trends suggest that algorithm selection should be guided by task requirements and signal characteristics rather than peak

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accuracy alone. Chart 1 illustrates the distribution of reported classification accuracies across three major algorithmic families (LSTM, SVM, and CNN) in the reviewed studies. While CNN-based approaches frequently occupy the upper range of reported accuracies, this visual comparison must be interpreted with caution: the underlying studies employed heterogeneous datasets, participant populations, validation protocols (intra- vs. cross-subject), and preprocessing pipelines. Importantly, these metrics reflect algorithmic performance under specific validation conditions and should not be conflated with therapeutic impact or functional recovery in clinical practice. Therefore, the chart primarily highlights a methodological trend the growing adoption of deep learning for end-to-end EEG representation learning rather than providing a statistically rigorous ranking of algorithmic superiority.

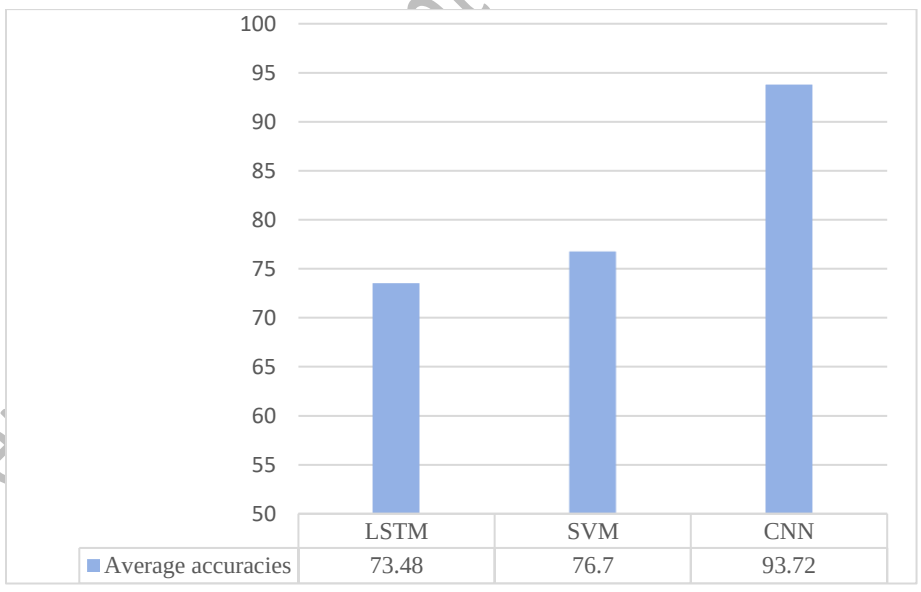


Chart (1): Comparison of Average Accuracy in Algorithms Used in Reviewed Articles

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The reviewed literature suggests that self-supervised learning (SSL) frameworks address core BCI challenges particularly calibration burden and cross-subject variability through mechanisms such as contrastive learning and masked autoencoding. Unlike conventional supervised methods that require large, labeled, subject-specific datasets, architectures like SpellerSSL(Hong et al., 2025) learn representations from unlabeled EEG data with the aim of improving generalization across subjects. Their potential advantage therefore extends beyond classification accuracy to reducing subject-specific calibration requirements and improving cross-subject generalization. By learning representations from unlabeled EEG signals, these approaches may reduce dependence on labeled, subject-specific training data and potentially improve robustness to inter-subject variability. Consequently, SSL represents a promising direction toward more scalable and user-independent BCI systems, although its clinical utility and long-term effectiveness require further validation in realistic rehabilitation settings.

The selection of a specific brain paradigm is typically dictated by the target rehabilitation outcome and user capabilities. As Table 3 illustrates, each paradigm presents distinct methodological trade-offs. Paradigm selection in rehabilitation contexts depends on the trade-off between technical feasibility, user training burden, and physiological compatibility. As summarized in Table 3, each approach presents distinct operational constraints that influence its real-world applicability.

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Table (3): Comparison of Brain Paradigms

Brain Paradigm	Applications	Advantages	Disadvantages	Training Time	Technical Challenges	Highest Reported Accuracy in Studies
Motor Imagery (MI)	Movement rehabilitation, neural stimulation	No need for external stimuli	Long training required, sensitivity to internal noise	High	Complexity of signal processing	93.2% in prosthetic control
SSVEP	Movement rehabilitation, wheelchair control, virtual rehabilitation	High transfer speed, high accuracy, low training requirement	Visual discomfort in users, dependence on stimuli	Very low	Need for precise display equipment	95% in movement control in VR
P300	Speech rehabilitation, control of communication devices	High accuracy, ease of use	Dependence on stimuli, need for user concentration, response delay	Low	Need for precise visual stimuli	99.81% in P300 spelling

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The performance differences among BCI paradigms reflect fundamental trade-offs between neurophysiological constraints and engineering feasibility. SSVEP achieves high accuracy (up to 95%) with minimal training by leveraging exogenous visual-evoked responses; however, this dependency limits applicability in patients with visual impairment. P300-based systems reach

exceptional accuracy in spelling tasks(Korkmaz et al., 2022), but require sustained attention and exhibit latency under cognitive load. Motor imagery, while demanding extensive user training and showing greater inter-subject variability, provides the only stimulus-free pathway to voluntary control—a critical feature for naturalistic motor rehabilitation. Its moderate average accuracy (e.g., ~78% in(Liu et al., 2024)) reflects the challenge of decoding endogenous sensorimotor rhythms rather than a fundamental limitation of the paradigm.

Importantly, accuracy values across paradigms represent technical performance under distinct validation frameworks and should not be viewed as directly equivalent indicators of real-world paradigm effectiveness. Differences in participant populations, task design, number of classes, EEG acquisition systems, preprocessing procedures, and validation strategies can substantially influence reported performance. Therefore, paradigm selection for rehabilitation should consider not only classification accuracy but also user training requirements, robustness, usability, accessibility, generalization across users, and clinically meaningful rehabilitation outcomes.

Discussion and Conclusion

This review highlights a persistent gap between advances in algorithmic performance and the practical clinical deployment of EEG-based brain-computer interface (BCI) systems for rehabilitation. Although classification accuracies and computational sophistication have improved substantially in recent years, many EEG-based BCI systems continue to operate primarily under controlled laboratory conditions, with limited evidence regarding long-term clinical reliability, ecological validity, and large-scale patient integration.

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The literature reveals a clear methodological shift from handcrafted feature pipelines toward end-to-end deep learning and self-supervised frameworks. Deep neural architectures, particularly convolutional neural networks, have demonstrated improved classification performance through their ability to learn complex spatiotemporal EEG representations automatically. Similarly, self-supervised approaches have addressed some limitations associated with subject-specific calibration and scarce labeled data by improving cross-subject generalization. However, the exceptionally high accuracies reported in many studies often rely on carefully controlled experimental conditions, creating a significant gap between laboratory performance and real-world clinical applicability.

The widespread preference for noninvasive EEG acquisition reflects the clinical need for safe, portable, and user-friendly systems. Commercial wearable EEG devices have facilitated more accessible rehabilitation environments, particularly in home-based and ecological settings. Nevertheless, practical deployment remains constrained by motion artifacts, environmental noise, limited spatial resolution, signal instability during prolonged use, and variations in patient attention, fatigue, and cognitive state. These challenges become increasingly pronounced in uncontrolled clinical environments and can substantially reduce decoding reliability.

Another recurring limitation is the phenomenon commonly referred to as BCI illiteracy, whereby a considerable proportion of users fail to generate sufficiently stable neural patterns for reliable system control. This issue underscores the limitations of relying solely on laboratory-based performance metrics when evaluating rehabilitation-oriented BCI systems. The reviewed literature further indicates that each EEG paradigm presents a distinct balance between usability, accuracy,

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training requirements, and physiological compatibility. SSVEP-based systems generally provide rapid and reliable control but depend on continuous visual stimulation. P300 paradigms have demonstrated strong performance in communication-oriented applications but require sustained attention and user engagement. Motor imagery systems often require longer training periods and exhibit greater inter-subject variability; however, they remain among the most clinically relevant approaches for neurorehabilitation because they directly engage endogenous motor networks and neuroplasticity mechanisms.

Beyond motor rehabilitation, emerging evidence suggests that EEG-based BCIs are increasingly being explored for broader neurological and assistive applications, including communication support, robotic and prosthetic control, neurofeedback interventions, and symptom management. Furthermore, the integration of BCIs with complementary technologies such as robotic rehabilitation platforms, virtual reality environments, and hybrid sensing modalities has shown potential for improving robustness, user engagement, and functional outcomes. Combining EEG with additional physiological signals may reduce ambiguity during real-world operation, while immersive rehabilitation environments can enhance motivation, adaptive feedback delivery, and training effectiveness.

Evidence from the reviewed studies indicates that no single BCI paradigm or classification architecture is universally optimal for rehabilitation contexts. The effectiveness of a system depends strongly on the intended clinical objective, environmental constraints, and user-specific characteristics. While advances in acquisition hardware, neural paradigms, and machine learning have significantly improved system capabilities, future progress will depend less on achieving

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incremental gains in benchmark accuracy and more on addressing the practical barriers that limit clinical adoption.

Future research should prioritize large-scale longitudinal validation, adaptive calibration strategies, reduced training requirements, improved robustness under ecological conditions, and user-centered system design. Hybrid sensing approaches, adaptive learning frameworks, and clinically meaningful outcome measures are likely to play an important role in enhancing real-world usability. Bridging the gap between experimental prototypes and routine clinical care will require sustained interdisciplinary collaboration among engineers, neuroscientists, clinicians, and end users, prioritizing reliability, accessibility, and patient-centered design.

Ethical Considerations

Ethical approval: This narrative review analyzed previously published, publicly available data and did not involve direct human or animal experimentation. Therefore, formal ethical approval was not required.

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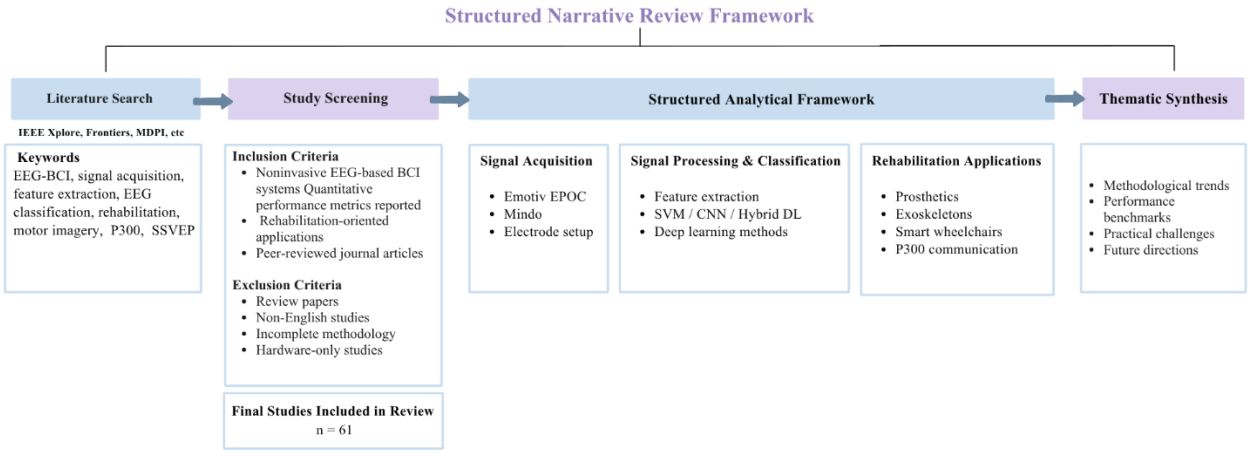
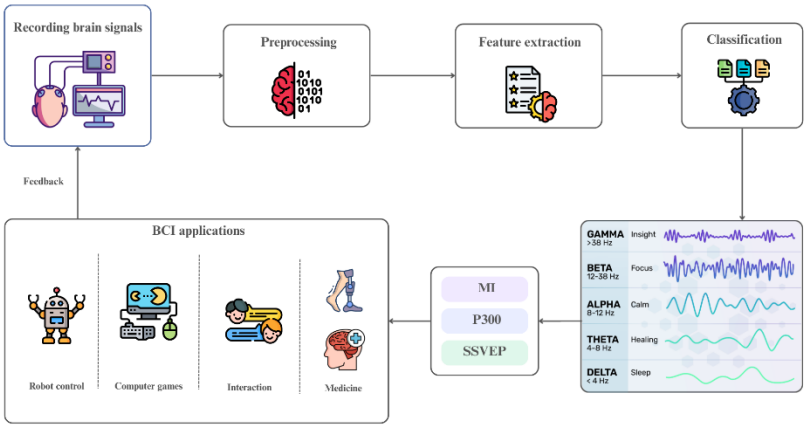
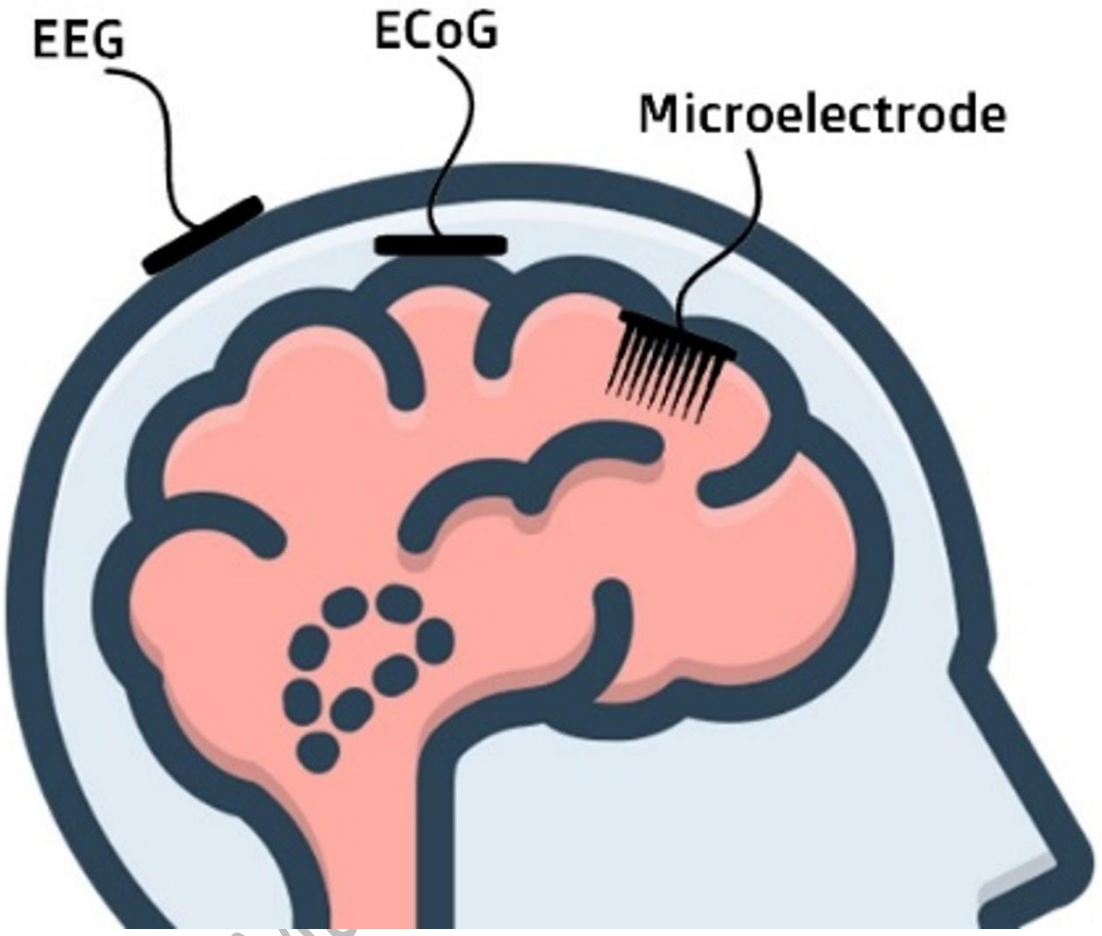


Figure1: Conceptual framework of the thematic synthesis. Studies were categorized into three domains acquisition hardware, signal processing/classification, and rehabilitation applications to enable comparative analysis of methodological trends.



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Figure 2: General workflow and major applications of EEG-based brain-computer interfaces (BCIs).



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Figure3: Electrode placement in EEG, electrocorticography (ECoG), and intracortical microelectrode recording systems. The figure compares the locations of recording electrodes in three major brain-computer interface modalities. EEG electrodes are placed noninvasively on the scalp, ECoG electrodes are positioned on the cortical surface beneath the skull, and intracortical microelectrodes are implanted directly into brain tissue. The spatial proximity of the electrodes to neural sources influences signal quality, spatial resolution, invasiveness, and clinical applicability.

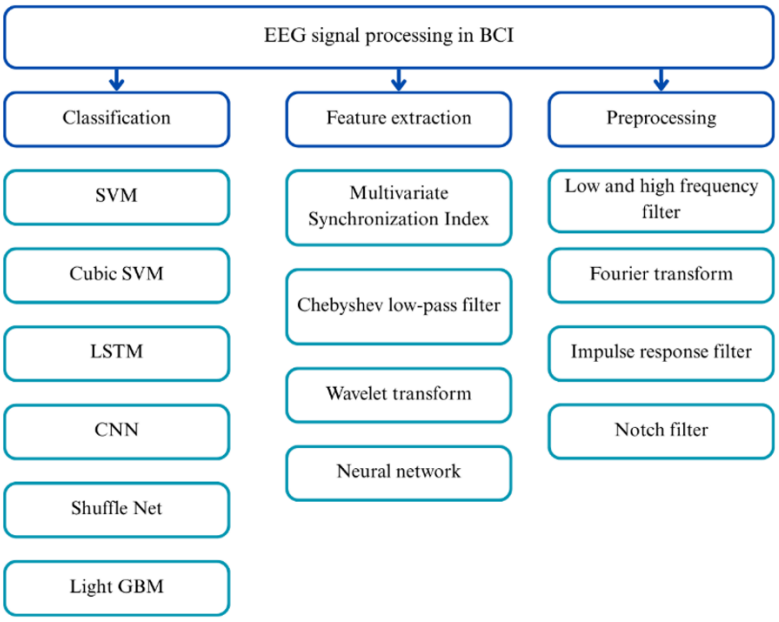


Figure 4: Overview of signal processing methods used in EEG-based brain-computer interfaces.The figure summarizes representative techniques employed at different stages of the EEG signal processing pipeline. Preprocessing methods are used to improve signal quality and remove artifacts, feature extraction techniques identify informative neural patterns, and classification algorithms translate extracted features into control commands. Common approaches reviewed in the literature for each processing stage are presented.

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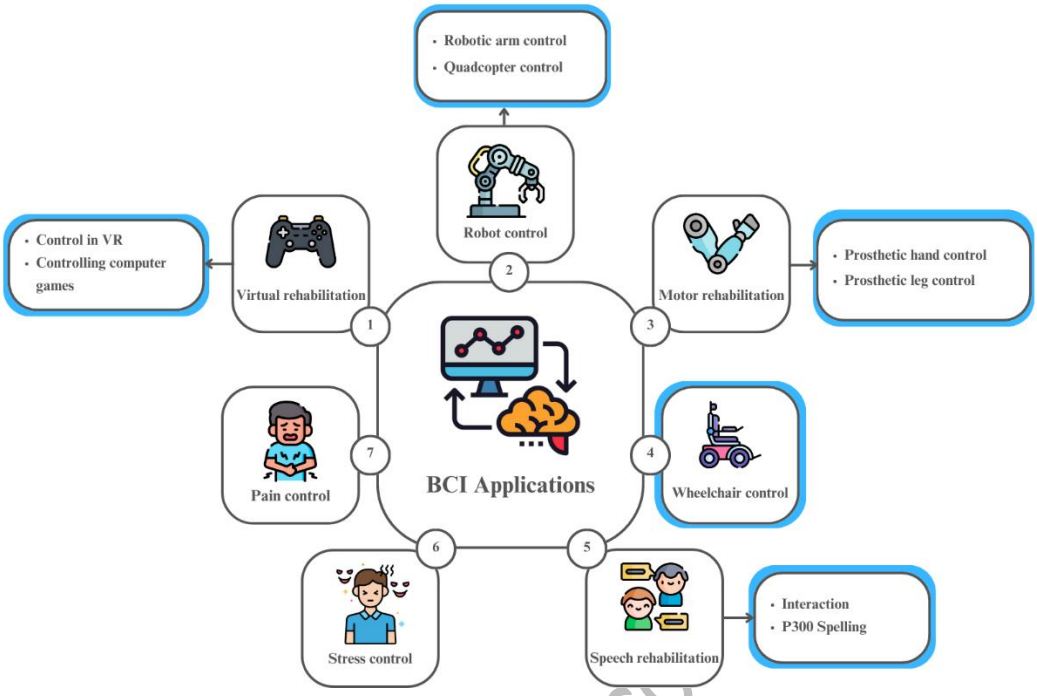


Figure 5: Summary of rehabilitation and assistive applications of brain-computer interfaces. The figure provides an overview of the major applications of brain-computer interface technologies reported in the reviewed literature. These applications include motor rehabilitation, communication and speech assistance, robotic and prosthetic device control, wheelchair navigation, neurofeedback training, and other assistive and therapeutic interventions. The figure highlights the broad potential of BCIs in improving functional independence and quality of life for individuals with neurological impairments.

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Authors	Brain Signal Paradigm	Feature Extraction Method	Classification Method	Accuracy
Cho et al. (Cho et al., 2021)	Motor Imagery	Bi-LSTM	Bi-LSTM	68%
Hong et al. (Hong et al., 2025)	P300	Self-supervised learning (1D U-Net)	self-supervised learning-1D UNet	94%
Liao et al. (Liao et al., 2025)	Motor Imagery	Transformers with TCN	transformers with TCN	74.48%
Bousseta et al. (Bousseta et al., 2018)	Motor Imagery	PCA and FFT	SVM	85.45%
Ghumman et al. (Ghumman et al., 2021)	---	Filter Bank CSP (FBCSP)	SVM	67.95%
Hameed et al. (Hameed et al., 2024)	Motor Imagery	Self-attention process	Transformer	BCI IV-2a = 88.75% BCI IV-2b = 84.20%
Huang et al. (Huang et al., 2022)	Motor Imagery	CNN	CNN	92%

Jia et al.(Jia et al., 2023)	Motor Imagery	Efficient Channel Attention	LIGHT GBM	86%
Liu et al. (Liu et al., 2024)	Motor Imagery	EEG MoE-Prob-Transformer (EMPT)	Transformer	95.24%
Sadiq et al. (Sadiq et al., 2022)	Motor Imagery	Continuous Wavelet Transform	CNN (ShuffleNet)	99.52%

Table 1 presents representative studies on EEG-based signal classification published during the review period. The table summarizes the classification approaches, EEG paradigms, datasets, feature extraction methods, validation protocols, and performance metrics reported in the selected studies, providing a comparative overview of methodological trends and evaluation strategies in EEG-based brain-computer interface research.

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Authors	Application Area	Brain Paradigm	Task	Success Rate
Leeb et al.(Leeb et al., 2007)	Virtual Rehabilitation	Beta Oscillations	Command "Go" from one virtual avatar to another	90%
Ortner et al.(Ortner et al., 2012)	Virtual Rehabilitation	Motor Imagery	Imagining hand movements in VR	90.4%
Lupu et al.(Lupu et al., 2018)	Virtual Rehabilitation	Motor Imagery	Controlling virtual characters in VR	85.44%
Zhang et al.(Zhang et al., 2015)	Virtual-Rehabilitation Robotics	SSMVEP	Moving a virtual person in four directions: backward, forward, left, and right	ACC: 85.6±10.1% ITR(bits/min): 10.72±4.82
Wang et al.(Wang et al., 2023)	Virtual Rehabilitation	SSVEP	Controlling 16 movements in VR	95%
Li et al.(Li et al., 2021)	Virtual Rehabilitation	P300	Playing and controlling the MindGomoku game	90.7%

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Amin et al. (Amin et al., 2022)	Virtual Rehabilitation	---	Shooting or not shooting at a target in therapeutic games for attention deficit treatment	89%
Xu et al. (Xu et al., 2020)	Robotics	Motor Imagery	Two tasks of imagining hand movements to grasp an object using a robotic arm	66.2±6% 78±6.1%
Kapgate et al. (Kapgate, 2022)	Robotics	SSVEP & P300	Flight control in a quadcopter: combining two types of brain potentials SSVEP and P300	Not reported
Kim et al. (Kim et al., 2021)	Motor Rehabilitation	Motor Imagery	Flexion and extension of the arm and hand	92.3%
Jochumsen et al. (Jochumsen et al., 2021)	Motor Rehabilitation	Motor Imagery	Inducing neural plasticity with a three-dimensional exoskeleton for the wrist	86±12%
Ma et al. (Ma et al., 2024)	Motor Rehabilitation	Motor Imagery	Four tasks: grasping with the left hand, grasping with the right hand, imagining	r = 0.399, P < 0.05

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			grasping with the left hand, and imagining grasping with the right hand.	
Nama et al. (Nama & Samanta, 2024)	Motor Rehabilitation	Motor Imagery	Two control commands on 36 target symbols	2.9% mean error:
Guo et al. (Guo et al., 2022)	Motor Rehabilitation	SSVEP	Hand function rehabilitation after stroke: Fugl-Meyer Assessment for Upper Extremity (FMA-UL), Wolf Motor Function Test (WMFT), and Modified Ashworth Scale (MAS)	full score: 10.05 ± 8.03, p = 0.001
Huang et al. (Huang, 2019)	Speech Rehabilitation	P300	Activation of the blinking button in the stereoscopic environment	96%
Qu et al. (Qu et al., 2018)	Speech Rehabilitation	P300	Activation of the blinking button in the	Not reported

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			stereoscopic environment	
Norzadeh et al.(Noorzadeh et al., 2020)	Speech Rehabilitation	P300	Activation of the blinking button for the Stereoscopic	73.25% - 74.65%
Korkmaz et al.(Korkmaz et al., 2022)	Speech Rehabilitation	P300	15 Blinks	99.81%
Fouad et al.(Fouad, 2021)	Speech Rehabilitation	P300	Blinking of Row Columns	90%

Table 2 summarizes the performance outcomes reported in rehabilitation-oriented EEG-based brain-computer interface studies. The table compares key characteristics of the selected studies, including target application, participant population, evaluation metrics, and reported performance measures, providing an overview of the effectiveness of BCI-assisted rehabilitation interventions.

Brain Paradigm	**Applications**	**Advantages**	**Disadvantages**	**Training Time**	**Technical Challenges**	**Highest Reported Accuracy in Studies**
Motor Imagery (MI)	Movement rehabilitation,	No need for external stimuli	Long training required,	High	Complexity of signal processing	93.2% in prosthetic control

	neural stimulation		sensitivity to internal noise			
SSVEP	Movement rehabilitation, wheelchair control, virtual rehabilitation	High transfer speed, high accuracy, low training requirement	Visual discomfort in users, dependence on stimuli	Very low	Need for precise display equipment	95% in movement control in VR
P300	Speech rehabilitation, control of communication devices	High accuracy, ease of use	Dependence on stimuli, need for user concentration, response delay	Low	Need for precise visual stimuli	99.81% in P300 spelling

Table 3 compares major brain-computer interface paradigms from multiple perspectives. The table summarizes the characteristics, advantages, limitations, signal requirements, training demands, information transfer capabilities, and typical applications of different BCI paradigms, providing a comprehensive overview of their suitability for rehabilitation and assistive technologies.

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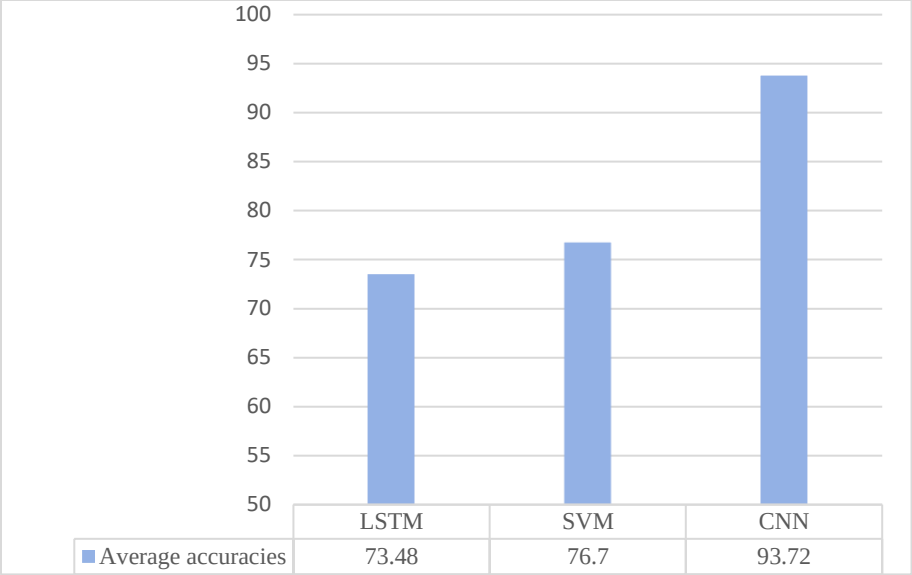


Chart 1: Distribution of reported classification accuracies across different classification algorithms. The chart summarizes the classification accuracies reported for LSTM-, SVM-, and CNN-based approaches in the reviewed studies. It provides an overview of the range and distribution of performance outcomes achieved by different algorithmic families in EEG signal classification tasks.

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