

Toward Deployable Neural Directional Control: Design Patterns and Evaluation Challenges

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Abstract. Real-time neural directional control is a key capability for brain-computer interface (BCI) systems supporting assistive mobility, robotic manipulation, and interactive environments. Although advances in signal processing and machine learning have improved neural decoding performance, deploying reliable directional control systems remains challenging due to neural variability, calibration requirements, and heterogeneous evaluation practices across studies.

This paper synthesizes recent developments in neural directional control systems with a focus on electroencephalography (EEG)-based BCIs while situating these systems within the broader landscape of neural interfaces. Using a structured literature synthesis following PRISMA guidelines, we analyze representative systems across assistive, robotic, and interactive applications. The analysis identifies recurring system design patterns including control granularity (discrete vs. continuous control), decoder architectures, and adaptation strategies for improving cross-subject generalization.

Our findings highlight a gradual transition from subject-dependent decoding pipelines toward calibration-efficient frameworks combining pre-trained models with lightweight adaptation. At the system level, shared-autonomy architectures and hybrid decoding pipelines increasingly support stable real-time interaction despite neural signal variability, while inconsistencies in evaluation protocols—particularly latency reporting, stability assessment, and longitudinal validation—continue to limit cross-study comparability.

Advancing deployable neural directional control systems will therefore require tighter integration between decoding algorithms, adaptive modeling strategies, and human-centered evaluation, alongside more standardized benchmarking practices for real-world BCI deployment.

Keywords: Brain-computer interface · EEG · Neural directional control · Real-time neural decoding · Human-centered AI · Assistive robotics

1 Introduction

Real-time neural-signal decoding for directional control represents one of the most compelling frontiers in brain-computer interface (BCI) research. From assistive wheelchairs and robotic manipulators to immersive interactive systems

and emerging neuroprosthetic platforms, translating neural activity into reliable directional commands has broad implications for mobility, accessibility, and human-machine integration [1,10,45,57,66]. Despite decades of progress, real-time neural directional control systems remain fragmented across domains, recording modalities, and evaluation frameworks.

Most research has focused on non-invasive electroencephalography (EEG), leveraging paradigms such as motor imagery (MI), steady-state visually evoked potentials (SSVEP), and P300 event-related potentials to enable directional commands in closed-loop systems [25,28,36,35,62,67]. Advances in adaptive filtering, deep learning architectures, and online calibration have improved decoding robustness under controlled laboratory conditions, while invasive neural recording technologies—including electrocorticography (ECoG) and intracortical micro-electrode arrays—demonstrate higher signal fidelity and lower latency. However, evaluation standards, reporting practices, and benchmarking perspectives remain highly heterogeneous across studies.

Existing surveys tend to examine isolated aspects of the field, including paradigm-specific reviews (e.g., motor imagery), application-specific analyses (e.g., gaming or wheelchair navigation), or algorithm-focused studies emphasizing advances in deep learning [28,35,36,59,60]. While valuable, these works rarely provide a unified cross-domain perspective integrating decoding robustness, cross-subject generalization, latency constraints, hardware variability, and human-centered usability considerations. Reproducibility practices—including dataset openness, transparency of preprocessing pipelines, and reporting of real-time latency—also remain inconsistently addressed.

To address this fragmentation, we conduct a systematic, modality-aware synthesis of real-time neural-signal directional control systems across application domains. The primary focus is on non-invasive EEG-based systems, which remain the most widely studied and practically deployable modality for directional BCIs [45,47,48,56,66]. Where relevant, we contextualize these findings with representative invasive neural recording studies to illustrate the broader performance spectrum of neural directional control technologies.

Beyond summarizing algorithmic trends, this work identifies recurring system design patterns across neural directional control studies and introduces a structured evaluation taxonomy capturing signal paradigms, decoding pipelines, adaptation strategies, latency characteristics, hardware configurations, and reproducibility indicators. This taxonomy enables cross-domain comparison of neural control systems and highlights architectural patterns that may influence real-time deployability and robustness.

Together, these elements support a structured investigation of neural directional control systems, leading to the three research questions that organize the remainder of the paper and the subsequent Results section.

The contributions of this paper are fourfold:

- A cross-domain, modality-aware systematic review of real-time neural directional control systems spanning assistive, robotic, and interactive applications.

- A methodological audit highlighting reporting inconsistencies in evaluation protocols, dataset accessibility, and deployment-related metrics.
- A unified evaluation taxonomy integrating decoding pipelines, latency constraints, adaptation mechanisms, and human-centered usability considerations.
- An evaluation taxonomy and benchmarking perspective to support more consistent comparison of neural directional control systems across modalities and application domains.

Research Questions

1. **RQ1:** Which signal processing and machine learning pipelines enable robust real-time neural decoding for directional control across recording modalities and application domains?
2. **RQ2:** How do adaptive modeling and cross-subject generalization strategies influence accuracy, latency, and deployment feasibility in real-time neural control systems?
3. **RQ3:** What evaluation and deployment practices (e.g., latency reporting, stability assessment, and adaptation strategies) are currently used in real-time neural directional control systems, and how can benchmarking frameworks improve comparability across studies?

2 Related Work

Prior research on neural-signal-based directional control spans multiple partially overlapping research streams. Existing work can broadly be categorized into four areas: (1) algorithm-focused reviews of neural decoding pipelines, (2) paradigm-specific analyses of neural control strategies, (3) application-oriented implementations in assistive and robotic systems, and (4) modality-specific investigations of neural recording technologies. Table 1 summarizes these research streams, their primary evaluation focuses, and the key limitations that motivate a more integrated cross-domain perspective.

Algorithm and Decoding Architectures

Early neural directional control systems relied heavily on classical signal processing techniques such as Common Spatial Patterns (CSP), band-power analysis, and autoregressive modeling for motor imagery (MI)-based classification. With the rapid development of deep learning, convolutional and recurrent neural network architectures have significantly improved spatial-temporal feature extraction for EEG decoding. Comprehensive surveys including [7,50,2,3,18,51,40] document the evolution of CNN- and RNN-based pipelines for EEG classification and highlight their increasing suitability for real-time BCI applications. More recent work has begun to explore subject-independent neural architectures designed to improve cross-user robustness, including subject-independent convolutional frameworks that reduce reliance on subject-specific calibration while maintaining competitive motor imagery decoding performance [52].

Category	Focus	Typical Evaluation	Key Limitations
Algorithm Reviews	Neural decoding architectures (CSP, CNN, RNN)	Classification accuracy, offline decoding	Limited deployment analysis and latency reporting
Paradigm Analyses	Neural paradigms (MI, SSVEP, P300)	Paradigm-specific performance metrics	Rare cross-paradigm comparison under real-time constraints
Application Systems	Assistive and robotic control implementations	Task success rate, user studies	Limited cross-domain benchmarking
Modality Investigations	Neural recording technologies (EEG, ECoG, iBCI)	Signal fidelity, decoding resolution	Few comparisons across invasive and non-invasive systems

Table 1. Major research streams in neural-signal directional control literature. Existing studies typically emphasize individual dimensions such as decoding algorithms, neural paradigms, application systems, or recording modalities. Cross-domain analyses integrating deployment constraints, latency, and reproducibility remain relatively limited.

Subsequent reviews further examine the integration of hybrid machine learning frameworks and task-specific decoder adaptations for assistive and robotic BCI systems [26]. These studies illustrate the rapid diversification of decoding architectures, ranging from classical signal processing pipelines to deep neural networks with attention mechanisms and multi-branch feature extraction.

More recently, attention has shifted toward calibration-efficient and cross-subject learning strategies. Cross-subject motor imagery decoding using leave-one-subject-out (LOSO) validation protocols has been investigated to quantify inter-user robustness [64]. To mitigate distribution shifts between users, domain adaptation and transfer learning techniques align feature representations across subjects. Discrepancy minimization strategies reduce inter-subject variance in latent spaces [21], while manifold-based transfer learning approaches perform structured alignment to support subject-independent MI decoding [4]. Adversarial adaptation has also been explored to learn subject-invariant representations under cross-subject evaluation, including Wasserstein-distance-based alignment objectives designed to improve training stability [55]. In parallel, domain-invariant representation learning constrains multi-scale neural features to remain stable across subjects, further reducing reliance on subject-specific calibration

[30]. Finally, plug-and-play transfer frameworks attempt to minimize calibration requirements through lightweight adaptation mechanisms [12]. Collectively, these studies reflect an increasing shift from subject-specific optimization toward deployable, calibration-efficient neural control systems.

Despite rapid advances in deep learning, practical implementations often continue to rely on classical signal-processing pipelines when prioritizing robustness and deployability. For example, a four-degree-of-freedom wheelchair control system built on a commercial Emotiv headset employs 8–40 Hz bandpass filtering with Mu and Beta sub-band decomposition prior to classification [17]. Such implementations highlight that traditional band-power-driven pipelines remain prevalent in real-world directional control deployments, even as deep architectures continue to evolve.

While algorithm-focused studies provide valuable insight into decoding performance and architectural innovation, they frequently emphasize classification accuracy while providing comparatively limited analysis of real-time latency constraints, system integration challenges, or deployment heterogeneity across assistive and robotic contexts.

Neural Control Paradigms

Another line of research focuses on paradigm-specific analyses of neural control strategies. Motor imagery (MI) remains one of the most extensively studied paradigms for non-invasive neural directional control. Surveys such as [38,40] highlight persistent challenges including signal non-stationarity, inter-subject variability, and calibration burden. In contrast, SSVEP- and P300-based systems rely on stimulus-driven neural responses and are often studied independently due to their distinct neurophysiological mechanisms and interaction paradigms.

Within MI-based control, most systems employ discrete command paradigms in which neural signals trigger directional selections such as left or right movement, while a smaller body of work investigates continuous neural modulation for velocity or trajectory control. For example, [61] proposes a shared-control framework in which MI-based EEG signals modulate robot velocity while autonomous navigation assists trajectory planning. This approach highlights the distinction between discrete command triggering and continuous neural modulation paradigms and demonstrates how shared autonomy can mitigate neural decoding uncertainty.

Although paradigm-specific analyses deepen understanding of individual signal types, they rarely compare discrete and continuous neural control strategies under common real-time constraints or across heterogeneous deployment scenarios. Consequently, systematic cross-paradigm comparisons of latency, robustness, and usability remain limited.

Application Systems and Deployment Contexts

Neural directional control has been explored across diverse application domains including interactive environments, assistive wheelchair navigation, mobile robotic

systems, and robotic manipulators. Recent work increasingly emphasizes system-level integration and human-centered evaluation metrics beyond classification accuracy, including user comfort, visual fatigue, engagement, and cognitive workload.

Several assistive systems illustrate the diversity of architectural strategies used in real-world deployments. A multimodal wheelchair platform integrating EEG-based attentiveness detection with EMG-based steering demonstrates the potential of hybrid biosignal fusion for directional control [58]. In parallel, shared-autonomy mobile robot systems combine neural modulation with simultaneous localization and mapping (SLAM) and dynamic window planning algorithms to support navigation in unknown environments [61]. More recently, noninvasive EEG-based systems have demonstrated real-time individual finger control of robotic hands using deep-learning decoders with online adaptation and smoothing mechanisms [8], highlighting a shift toward fine-grained effector-level control.

These implementations illustrate the growing complexity of integrated neural control systems. However, application-oriented studies often evaluate systems within specific domains, limiting opportunities for cross-domain benchmarking and systematic comparison of operational characteristics such as latency, calibration time, and long-term stability.

Recording Modalities and Hardware Constraints

Most existing reviews focus predominantly on non-invasive EEG systems due to their safety, accessibility, and portability advantages. Even within non-invasive systems, substantial heterogeneity exists in sensor configurations, signal quality, and hardware integration. Hybrid EEG–EMG configurations have been proposed to improve robustness by combining neural intent signals with muscle activity measurements [58], while shared-control strategies mitigate neural variability by incorporating autonomous robotic assistance [61].

Beyond scalp EEG, minimally invasive neural interface technologies are emerging to balance signal fidelity and surgical burden. These systems aim to improve spatial resolution and stability while avoiding the full implantation complexity of intracortical microelectrode arrays [19]. Such approaches position minimally invasive technologies between non-invasive EEG and fully implanted intracortical systems along a translational continuum of neural control modalities.

Fully invasive neural recording modalities—including electrocorticography (ECoG) and intracortical microelectrode arrays—have demonstrated high-resolution neural decoding and continuous kinematic control in closed-loop experiments. Intracortical systems leveraging motor cortex recordings have enabled real-time velocity decoding and multidimensional robotic control in both human and non-human primate studies, often employing Kalman-filter-based or neural-network-based decoders.

Recent methodological overviews emphasize feature engineering strategies, calibration procedures, and adaptive decoder updating mechanisms for maintaining long-term neural control stability [9]. Systematic surveys of invasive BCI systems further highlight the diversity of neural signal types, control targets,

and validation paradigms across preclinical and translational research settings [15]. Roadmap analyses additionally identify key translational challenges such as decoder robustness, automatic recalibration, and sustained home-use feasibility for clinical iBCI deployment [11].

Despite these advances, invasive and non-invasive neural control systems are frequently analyzed within separate research communities. Cross-modality comparison of latency reporting, control dimensionality, adaptation strategies, and reproducibility practices remains limited in the existing literature.

Reproducibility and Benchmarking Challenges

Across algorithm-, paradigm-, application-, and modality-focused studies, reporting practices vary considerably. Differences in preprocessing pipelines, subject calibration procedures, hardware configurations, and latency measurement methodologies complicate direct comparison between studies. Although previous surveys acknowledge challenges related to neural signal non-stationarity and adaptation [38,40], structured assessments of dataset accessibility, cross-subject validation strategies, code availability, and real-time benchmarking protocols remain relatively rare.

Motivated by these gaps, the present study adopts a cross-domain and modality-aware perspective on real-time neural directional control systems. By integrating algorithmic trends, control paradigms (discrete, continuous, and shared autonomy), hardware variability, adaptation mechanisms, and reproducibility indicators within a unified evaluation taxonomy, this work aims to provide a more systematic basis for comparing neural directional control systems. In addition, we outline a lightweight benchmarking framework intended to support standardized evaluation of decoding pipelines under comparable experimental conditions, thereby bridging the gap between methodological innovation and deployable neural control technologies.

3 Method

This study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure transparency and reproducibility [39]. A structured literature search was conducted to identify studies related to EEG-based neural directional control in gaming, assistive technologies, and robotic applications.

Search Strategy

A structured literature search was conducted across five major academic databases—Google Scholar, PubMed, Web of Science, ACM Digital Library, and IEEE Xplore—covering the period from 2013 to 2025. Boolean keyword combinations were developed based on EEG paradigms, signal processing techniques, machine learning architectures, and application contexts.

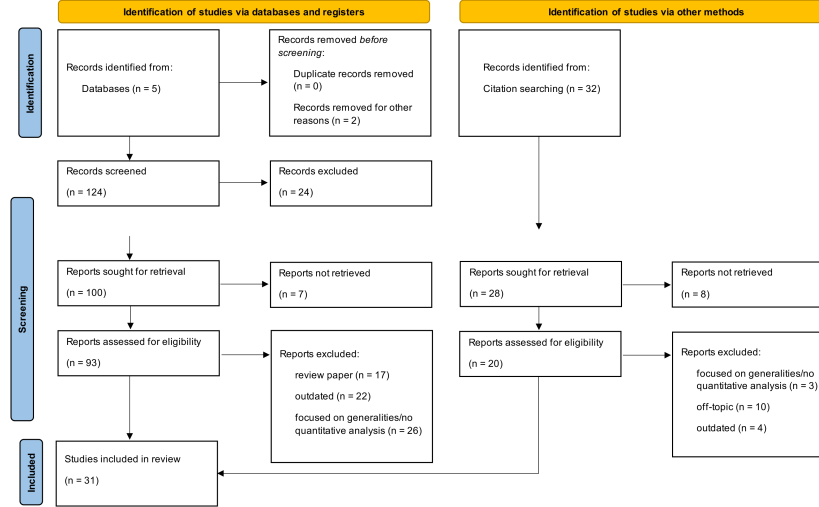


Fig. 1. PRISMA 2020

The keyword categories used in the search process are summarized in Table 2. These categories capture common terminology used in neural decoding, real-time BCI systems, and human-centered evaluations.

Study Screening and Eligibility

The screening process followed the PRISMA workflow illustrated in Figure 1. A total of 168 records were initially identified through database searches. Duplicate entries were removed prior to title and abstract screening. Studies were screened using the inclusion and exclusion criteria summarized in Table 3.

Studies were retained if they implemented EEG-based brain–computer interface methods for directional or continuous control in gaming, assistive, or robotic applications. Both real-time systems and simulation-based pipelines relevant to online decoding were considered.

After full-text assessment, 31 publications were retained for detailed analysis. These studies span multiple EEG paradigms—including motor imagery (MI), SSVEP, and P300—and cover applications such as BCI gaming, wheelchair navigation, and robotic control systems.

Category	Example Keywords	Search Frequency
EEG Paradigms	motor imagery (MI); SSVEP; P300; event-related potentials (ERP); directional control	High
Signal Processing	band power; common spatial patterns (CSP); ICA; adaptive filtering; feature extraction	High
Machine Learning	CNN; RNN; transformer; SVM; hybrid models; neural decoding	High
Real-Time Systems	online decoding; closed-loop control; real-time BCI; feedback loop	Medium–High
Human–Centered Evaluation	usability; comfort; engagement; cognitive workload; user adaptation	Medium
Assistive Applications	wheelchair control; robotic arm; exoskeleton; prosthetic navigation	Medium
Gaming Applications	EEG game; BCI gaming; virtual navigation; interactive gameplay	Medium
Evaluation Metrics	accuracy; F1-score; latency; information transfer rate (ITR)	Medium

Table 2. Keyword categories used to construct the PRISMA search queries for identifying studies on EEG-based neural directional control systems. Frequency indicates the relative prevalence of each keyword category during the search process.

Data Extraction and Study Coding

For each selected study, structured information was extracted to support systematic comparison across neural directional control systems. Extracted attributes included the neural paradigm, EEG hardware configuration, signal processing pipeline, machine learning architecture, evaluation metrics, and human-centered outcomes such as usability and cognitive workload.

Table 4 summarizes the primary variables used to code each study during the review process.

Quality Assessment

To ensure methodological consistency, studies were qualitatively assessed for reporting completeness and potential sources of methodological bias. The assessment focused on several reproducibility indicators, including clarity of experimental protocol descriptions, availability of dataset information, transparency of preprocessing and feature extraction pipelines, validation procedures (e.g., cross-validation or cross-subject evaluation), and reporting of key performance metrics such as accuracy, latency, and information transfer rate (ITR). These factors were used as qualitative indicators of methodological transparency rather than as a numerical scoring system. Studies lacking sufficient experimental detail or reproducibility information were excluded during the screening stage.

Screening Criterion	Decision
Study applies EEG-based brain-computer interface (BCI) methods for directional or continuous control in gaming, assistive, or robotic applications	Include
Study implements real-time or simulation-based neural decoding pipelines relevant to online BCI control	Include
Study evaluates machine learning algorithms (e.g., CSP, CNN, RNN, transformer, or hybrid models) for EEG signal decoding	Include
Study reports quantitative performance metrics such as accuracy, latency, or information transfer rate (ITR)	Include
Study describes EEG hardware configuration and includes human participant experiments	Include
Study reports human-centered evaluation factors such as usability, comfort, workload, or user adaptation	Include
Study focuses on non-directional EEG tasks (e.g., emotion recognition, ERP-only analysis, clinical diagnosis)	Exclude
Study lacks methodological transparency, experimental detail, or reproducibility information	Exclude

Table 3. Inclusion and exclusion criteria applied during the PRISMA screening process for selecting studies on EEG-based neural directional control systems.

Scope of Neural Modalities

While the primary focus of this synthesis is EEG-based neural directional control systems due to their accessibility and widespread use in BCI applications, representative invasive neural interface studies (e.g., ECoG and intracortical recordings) were also examined qualitatively. These comparisons provide contextual insights into the broader landscape of neural control technologies and help situate EEG-based systems within the wider performance spectrum of neural decoding approaches, particularly with respect to signal fidelity and real-time control latency.

These comparisons help situate EEG-based systems within the larger spectrum of neural decoding performance, particularly regarding signal fidelity and real-time control latency.

Variable	Description
Paradigm	MI, SSVEP, P300, or hybrid neural paradigm
Decoder Architecture	CSP+SVM, CNN, RNN, transformer, or hybrid model
Control Type	Discrete directional commands or continuous control
Evaluation Metrics	Accuracy, ITR, latency, classification rate
Generalization Strategy	Subject-dependent, LOSO, or transfer learning
Hardware Platform	Research-grade EEG or consumer EEG device
Human Factors	Usability, comfort, workload, engagement

Table 4. Variables extracted during the study coding process to support cross-study comparison of neural directional control systems.

4 Results

The selected studies reveal several recurring system-design patterns in neural directional control. To organize these findings, we analyze the literature along three dimensions corresponding to the research questions of this review: (RQ1) system design and control paradigms including control granularity, effectors, and decoding pipelines; (RQ2) cross-subject and cross-session generalization strategies that reduce calibration requirements; and (RQ3) practical deployment considerations such as latency, stability, and long-term adaptation.

4.1 Control Granularity: Discrete vs Continuous Neural Control (RQ1)

Across the reviewed studies, neural directional control systems can be broadly categorized according to *control granularity*, that is, whether neural signals trigger discrete directional commands or continuously modulate movement variables such as velocity or trajectory. This distinction influences system design, including decoder architecture, latency tolerance, calibration procedures, and the level of shared autonomy required for stable operation.

Discrete command-based control. Discrete control systems classify neural activity into a small set of predefined commands (e.g., left, right, forward). Such approaches are common in EEG-based brain-computer interface (BCI) systems because classification pipelines are comparatively simple and robust to neural variability. For example, motor imagery (MI) decoding combined with band-power features and linear classifiers has been used to implement four-direction wheelchair navigation in consumer-grade EEG setups [17]. Similar discrete command paradigms appear frequently in assistive navigation and hybrid robotic control systems where predictable command structures improve operational safety.

Continuous velocity modulation. Continuous control systems instead map neural signals to proportional variables such as velocity. In shared-control mobile robot navigation, MI-based EEG signals can modulate robot velocity while an autonomous navigation layer manages path planning and obstacle

avoidance [61]. Continuous decoding approaches are also common in invasive neural interfaces, where higher signal fidelity enables real-time estimation of kinematic variables such as velocity or cursor position [13,20,43]. Compared with discrete control, continuous paradigms typically require more stable decoders and stricter timing constraints.

Trajectory reconstruction and error-aware control. More advanced paradigms integrate trajectory reconstruction with online error monitoring. In these systems, neural signals generate motion commands while error-related potentials signal incorrect system behavior. For example, EEG-based frameworks combining trajectory decoding with asynchronous error-related potential detection have demonstrated closed-loop cursor control capable of correcting movement errors in real time [34]. These hybrid paradigms illustrate how neural feedback can improve reliability in closed-loop interaction.

4.2 Effector Type and Control Target (RQ1)

Another important dimension of neural directional control systems is the type of *effector* being controlled. Across the reviewed studies, neural signals are used to operate both virtual interfaces and physical assistive or robotic platforms. The type of effector influences system design, including the required control dimensionality, latency constraints, and the level of autonomous assistance incorporated into the control loop.

Cursor-based control. Cursor control tasks remain a common benchmark paradigm for studying neural trajectory decoding and closed-loop feedback. Although cursor environments are virtual, they provide controlled conditions for evaluating decoding algorithms, latency, and longitudinal stability. Several intracortical BCI studies have used cursor tasks to investigate long-term decoder performance and neural signal variability across weeks or months of deployment [20,43]. Cursor paradigms are also frequently used in EEG-based systems to evaluate real-time control pipelines and error-related neural responses [34].

Wheelchair and mobile robot navigation. Assistive mobility represents one of the most widely explored real-world applications of neural directional control. EEG-based motor imagery systems have been used to implement discrete multi-direction wheelchair steering using consumer-grade EEG hardware [17]. In more advanced systems, neural signals are combined with autonomous navigation algorithms to form shared-control frameworks in which the user modulates motion direction or velocity while the robotic platform manages obstacle avoidance and path planning [61]. Multimodal fusion approaches combining EEG with additional physiological signals such as EMG have also been proposed to improve steering robustness in assistive mobility scenarios [58].

Robotic arm and manipulation systems. Neural directional control has also been applied to robotic manipulation tasks. Hybrid asynchronous BCI systems integrating EEG, EOG, and computer vision have enabled shared-control reach-grasp operations for robotic arms [65]. In addition, deep-learning-based EEG decoders have demonstrated the feasibility of reconstructing fine-grained hand or finger movements for robotic or prosthetic control [8]. Intracortical BCI

Ref	Mod	Eff	Ctrl	Dec	Adapt	DOF
[17]	EEG	WC	Disc	BP+Cls	Subj	4
[61]	EEG	MR	Cont-V	MI+Plan	2-stage	2D
[58]	EEG+EMG	WC	Hybrid	Fusion	Calib	2D
[65]	EEG+EOG	Arm	Shared	Async	None	3D
[8]	EEG	Hand	Cont-T	DNN	Fit	Finger
[34]	EEG	Cursor	Cont+ErrP	Reg+Cls	Calib	2D
[13]	iBCI	Prost	Cont-K	KF	Update	Multi
[20]	iBCI	Cursor	Cont-K	LSTM	Fixed	2D
[43]	iBCI	Cursor	Cont-K	LSTM	Drift-Metric	2D
[23]	iBCI	Cursor	Cont-K	Align+Lin	Align	2D

Table 5. Representative neural directional control systems illustrating modality, effector type, control paradigm, decoder architecture, adaptation strategy, and control dimensionality. Abbreviations: Mod = neural modality; Eff = effector (WC: wheelchair, MR: mobile robot); Ctrl = control paradigm; Dec = decoder architecture; Adapt = adaptation strategy; DOF = control dimensionality.

systems extend these capabilities further by decoding continuous kinematic variables for multi-degree-of-freedom prosthetic control [13,23].

To illustrate the diversity of representative systems across modalities, effectors, and control strategies, Table 5 summarizes key system-level characteristics including neural modality, effector type, control paradigm, decoder architecture, adaptation strategy, and control dimensionality.

4.3 Decoder Architectures and Signal Processing Pipelines (RQ1)

Neural directional control systems rely on signal processing pipelines that transform raw neural recordings into control variables such as directional commands or continuous kinematic estimates. Across the reviewed studies, decoding pipelines range from classical feature-based approaches to modern deep-learning architectures designed to capture nonlinear neural dynamics.

Feature extraction and linear decoding. Traditional EEG-based systems typically employ frequency-band analysis and spatial filtering to extract discriminative neural features. Common approaches include band-power estimation within the mu and beta rhythms and spatial filtering techniques such as Common Spatial Patterns (CSP). These features are then classified using linear models or support vector machines to generate discrete directional commands. Such pipelines remain widely used in motor imagery BCI systems due to their computational efficiency and interpretability [17].

Regression-based continuous decoding. Continuous neural control often requires estimating kinematic variables such as velocity or position. In these settings, regression-based decoders and state-space models are commonly used. Kalman filters, for example, map neural activity to velocity estimates and update control outputs at fixed time intervals, enabling smooth real-time cursor or pros-

Ref	Feature Representation	Decoder Type	Nonlinear	Closed-Loop
[17]	Band power	Linear classifier	No	Yes
[61]	MI features	Hybrid + planner	Partial	Yes
[8]	Learned deep features	Neural network	Yes	Yes
[13]	Spike features	Kalman filter	No	Yes
[34]	MRCP + ErrP	Regression + classifier	Partial	Yes
[20]	Spike rates	LSTM	Yes	Yes
[23]	Neural manifold	Alignment + linear	Partial	Yes

Table 6. Decoder architecture and feature taxonomy across representative systems.

thetic control [13]. These approaches are particularly prevalent in intracortical BCI systems where neural spike features provide higher temporal resolution.

Neural network and representation-learning models. Recent studies increasingly explore deep learning architectures to capture nonlinear relationships between neural signals and control variables. Neural networks can automatically learn hierarchical representations from EEG or spike-based features, improving decoding robustness under complex neural variability [8]. Recurrent neural networks trained on multi-session historical data have demonstrated improved stability in long-term neural cursor control experiments lasting several months [20]. More recently, unsupervised manifold alignment techniques have been proposed to stabilize neural representations across recording sessions by aligning neural population activity over time [23].

Although the primary focus of this review is EEG-based neural directional control, representative intracortical BCI systems are included to illustrate broader decoder design trends across neural modalities. Table 6 summarizes the taxonomy of feature representations and decoder architectures across representative systems.

4.4 Latency, Update Rate, and Closed-Loop Performance Reporting (RQ1)

Real-time neural directional control requires tight timing constraints between neural signal acquisition, decoding, and actuator response. Across the reviewed studies, however, reporting practices for latency and update frequency vary considerably. Some studies explicitly report neural decoding bin sizes or control update rates, while others only provide qualitative descriptions of real-time performance.

In EEG-based systems, control updates are often limited by signal preprocessing and feature extraction pipelines. Typical implementations operate at update intervals ranging from approximately 100–300 ms, balancing responsiveness with the need for stable feature estimation. Discrete command-based systems are generally more tolerant of longer update cycles because commands are triggered intermittently rather than continuously.

Study	Neural Modality	Decoder Update	Control Paradigm	Shared Autonomy
[17]	EEG	~200–300 ms	Discrete MI control	No
[61]	EEG	~100–200 ms	Continuous velocity	Yes
[34]	EEG	~100 ms	Trajectory + ErrP	No
[20]	iBCI	20–50 ms bins	Continuous kinematics	No
[13]	iBCI	20–50 ms bins	Continuous kinematics	No

Table 7. Representative reporting practices for decoder update intervals and closed-loop timing in neural directional control systems. Shared autonomy indicates whether autonomous navigation or planning assists neural control.

In contrast, continuous neural control systems require more frequent update cycles to maintain smooth movement trajectories. Intracortical BCI systems frequently employ fixed decoding bins on the order of 20–50 ms, enabling high-frequency updates for cursor or prosthetic control [20,13]. Such high update rates support fine-grained kinematic estimation but require stable neural recordings and efficient decoding pipelines.

Another important aspect of closed-loop performance is the integration of autonomous assistance. Shared-control systems often combine neural input with robotic planning algorithms, allowing neural signals to modulate movement direction or velocity while the robotic platform ensures safe navigation [61]. This hybrid control structure can partially compensate for latency and variability in neural decoding.

Table 7 summarizes representative reporting practices for update frequency and latency across neural directional control systems.

4.5 Longitudinal Stability, Drift, and Recalibration (RQ1 Deployment Challenges)

A major challenge for real-time neural directional control systems is maintaining stable decoding performance over extended periods of use. Neural signals are inherently non-stationary, and variations in electrode placement, physiological state, or neural adaptation can gradually degrade decoder accuracy. As a result, many early BCI systems relied on frequent recalibration sessions to maintain reliable control.

Decoder drift and session variability. Longitudinal studies of intracortical BCIs demonstrate that neural population activity can change across days or months, leading to gradual decoder drift if models remain fixed. For example, multi-session cursor control experiments using recurrent neural network decoders showed high closed-loop performance for several months before performance degradation began to emerge due to neural variability [20]. Similar challenges have also been observed in EEG-based motor imagery systems, where session-to-session variability can significantly reduce classification accuracy when models trained on earlier sessions are applied without recalibration [5].

Instability measurement and adaptive recalibration. Recent work has explored methods for quantifying neural signal instability in order to determine when recalibration may be necessary. The MINDFUL framework, for instance, proposes metrics that estimate decoder instability by analyzing changes in neural representations over time. Experiments conducted over deployments lasting several weeks to months showed strong correlations between instability metrics and decoding performance degradation, suggesting that such measures could guide adaptive recalibration strategies [43].

Representation alignment and decoder stabilization. Another promising direction involves stabilizing neural representations across sessions rather than repeatedly retraining decoders. Manifold-alignment approaches attempt to align neural population activity across recording sessions, preserving the relationship between neural signals and control variables even when neural representations shift. Such techniques have demonstrated improved long-term stability in neural cursor control systems without requiring daily recalibration [23]. These approaches highlight a broader trend toward representation-level adaptation strategies designed to improve the practical deployability of neural control systems.

4.6 Adaptation and Calibration Strategies (RQ1 Deployment Challenges)

Calibration remains a critical factor affecting the practical deployment of neural directional control systems. Many EEG-based motor imagery BCIs rely on subject-specific training sessions to learn individualized neural patterns before real-time operation can begin [17]. While such calibration procedures improve decoding accuracy, they also introduce usability challenges, particularly in assistive scenarios where repeated setup sessions may be impractical. Continuous control systems often require additional model fitting or parameter tuning to maintain stable performance across sessions [61].

To reduce calibration burden, recent research has explored adaptive decoding strategies that maintain performance under neural variability. These include incremental model updates and representation learning methods that encourage session-invariant features across recording sessions [63]. Such approaches aim to balance decoding accuracy with deployment efficiency, motivating a growing body of work on cross-subject generalization and calibration-efficient neural decoding frameworks. While these strategies address session-level variability, an equally important challenge is enabling neural control systems to generalize across different users with minimal calibration. This motivates the research question addressed in the following section.

4.7 Cross-Subject and Cross-Session Generalization (RQ2)

A key limitation of many neural directional control systems is their dependence on subject-specific calibration. Traditional EEG-based motor imagery BCIs often require individualized training sessions before reliable control can be achieved

Ref	Evaluation Protocol	Adaptation Mechanism	Calibration Need	Target Scenario
[64]	LOSO cross-subject	Subject-independent training	Minimal	General MI decoding
[21]	Cross-subject transfer	Feature alignment	Reduced	Domain adaptation
[12]	Plug-and-play setup	Transfer layer	Low	Rapid deployment
[29]	LOSO cross-subject	Multi-domain transfer learning	Reduced	Cross-subject MI decoding
[32]	Cross-subject pretraining	Self-supervised representation learning	Reduced	Subject-invariant EEG features
[24]	Cross-subject evaluation	Compact deep neural network	Low	Efficient MI decoding
[16]	Longitudinal cross-session evaluation	Transfer learning calibration reduction	Low	Session-adaptive MI decoding
[6]	Single-source single-target transfer	Multi-subdomain domain adaptation	Reduced	Cross-session MI generalization

Table 8. RQ2: Cross-subject generalization strategies and calibration requirements in representative BCI systems.

[17]. This calibration requirement limits scalability and reduces usability in real-world assistive or consumer scenarios. Recent work therefore focuses on improving cross-subject generalization and reducing the need for extensive per-user training.

Table 8 summarizes representative approaches addressing cross-subject generalization through transfer learning, feature alignment, and calibration-efficient adaptation strategies.

Recent studies further emphasize the importance of addressing both cross-subject and cross-session variability in practical BCI deployment. For example, [33] introduced a large-scale multi-day motor imagery dataset designed to analyze session-to-session variability and benchmark adaptation strategies across recording days. Complementary work explores transfer learning approaches that explicitly reduce calibration requirements. For instance, [16] demonstrated that transfer learning can substantially reduce session-specific calibration effort while maintaining decoding performance in longitudinal motor imagery experiments. Similarly, domain adaptation techniques such as the multi-subdomain adaptation framework proposed by [6] aim to mitigate temporal distribution shifts across sessions and users, enabling models trained on prior data to generalize more effectively to new participants. Together, these studies highlight the growing emphasis on calibration-efficient and transferable neural decoding pipelines.

These methods aim to balance decoding accuracy with practical deployment constraints by enabling models trained on prior users or datasets to adapt efficiently to new participants [8,34,61].

Overall, the literature suggests a gradual shift from fully subject-dependent decoding pipelines toward calibration-efficient frameworks that combine pre-trained models with lightweight user adaptation. Such strategies represent an important step toward scalable neural control interfaces capable of supporting diverse users with minimal setup.

Ref	Signal Modality	Control Task	Evaluation Metrics
[17]	EEG	Wheelchair navigation	Accuracy, task success
[61]	EEG	Continuous cursor control	trajectory error, latency
[8]	EEG	Hand gesture decoding	classification accuracy
[20]	Intracortical	Cursor control	target acquisition rate
[23]	Intracortical	Cursor control	stability, trajectory error
[54]	EEG	Motor imagery classification	accuracy, inference latency
[14]	EEG	Human-computer interaction task	cognitive workload, usability

Table 9. Representative evaluation protocols and performance metrics used in neural directional control studies.

4.8 Evaluation Protocols and Performance Assessment (RQ3)

Evaluating neural directional control systems presents unique challenges due to differences in signal modality, task design, and experimental protocols. Studies vary widely in their choice of datasets, control tasks (e.g., cursor control, robotic manipulation, or prosthetic movement), and evaluation metrics. As a result, direct performance comparison across studies is often difficult, and several recent reviews have called for more standardized evaluation frameworks for closed-loop BCI systems [22,41]. In addition, variability in user performance and session-to-session dynamics can further complicate evaluation and interpretation of BCI system results [37].

Table 9 summarizes representative evaluation protocols used in recent work. These protocols differ in terms of signal modality, control tasks, and performance metrics, reflecting the diversity of application scenarios in neural control research [8,17,20,61,27].

Despite this diversity, several common evaluation dimensions emerge, including task success rate, decoding accuracy, trajectory error, and closed-loop response latency. These metrics provide complementary perspectives on system performance and usability, particularly in real-time assistive control settings. Recent work has also emphasized the importance of computational efficiency and deployment feasibility. For example, latency-aware optimization strategies can substantially reduce inference time while maintaining competitive decoding accuracy, enabling more responsive real-time BCI systems [54].

Overall, current evaluation practices highlight the importance of task-specific performance metrics and closed-loop testing. While accuracy-based metrics remain common in offline decoding studies, real-time systems increasingly emphasize usability-oriented measures such as response latency, trajectory stability, and task completion rate. In addition to performance metrics, recent studies have begun incorporating human-centered evaluation factors such as cognitive workload and user experience to better understand how neural control systems perform during interactive tasks [14]. These evaluation considerations are critical for translating neural directional control systems from laboratory demonstrations to practical assistive technologies and real-world deployment scenarios [27].

5 Discussion

The results of this review highlight several emerging design patterns for real-time neural directional control systems within broader human-centered AI and interactive computing contexts [31,46,44,49,53]. By synthesizing architectural characteristics (RQ1), cross-subject generalization strategies (RQ2), and evaluation practices (RQ3), several practical design considerations can be identified for developing deployable EEG-based directional BCIs. Rather than proposing a new decoding algorithm, this study aims to distill methodological insights and system-level design guidance that can inform future development of practical neural control interfaces [1,10,25,57,62,67].

5.1 Design Considerations for Real-Time EEG Directional BCIs

The surveyed literature suggests several core considerations when designing real-time neural directional control systems.

Control paradigm selection. Directional BCIs typically adopt either discrete command classification or continuous trajectory decoding. Discrete motor imagery classification remains easier to deploy and more robust under noisy EEG conditions, whereas continuous decoding enables smoother interaction but requires higher signal quality and more sophisticated decoders.

Feature representation and decoding. Reliable feature extraction pipelines remain essential for stable real-time performance. Classical approaches based on frequency-band decomposition and spatial filtering are widely used due to their robustness and interpretability, while deep neural architectures may improve nonlinear feature learning when sufficient training data is available.

Generalization and deployment robustness. Inter-subject variability and session drift remain major challenges for EEG BCIs. Recent work explores subject-independent training, feature alignment, and transfer learning frameworks to reduce calibration overhead [64,21,12]. Longitudinal studies also highlight the importance of adaptive recalibration or representation stabilization to maintain performance over time [42].

Table 10 summarizes the main design considerations derived from the surveyed literature.

5.2 Limitations and Future Research

Despite progress in neural decoding algorithms and system architectures, several limitations remain in the current literature. First, many studies evaluate systems using short experimental sessions or offline datasets, providing limited insight into long-term deployment stability. Second, evaluation protocols and performance metrics vary widely across studies, making direct comparison difficult and highlighting the need for more standardized benchmarking practices.

Future research should prioritize larger multi-session datasets and standardized evaluation protocols to better assess real-world usability and long-term robustness of neural directional control systems.

Design Stage	Recommended Practice
Control Paradigm	Choose discrete MI or continuous decoding based on task needs
Feature Representation	Use band-power + spatial filtering or deep neural features
Generalization	Evaluate cross-subject robustness (e.g., LOSO validation)
Deployment	Combine neural decoding with shared autonomy when controlling devices

Table 10. Recommended design practices for real-time EEG directional BCI systems derived from surveyed literature.

6 Conclusion

This systematic review synthesized recent research on real-time neural directional control systems across assistive, robotic, and interactive applications. Addressing **RQ1**, the reviewed studies reveal several dominant system-design patterns. Most EEG-based systems rely on discrete command classification pipelines built on band-power features and spatial filtering, while continuous control approaches—more common in invasive neural interfaces—support smoother trajectory modulation but require higher signal fidelity and stricter latency constraints. Hybrid shared-autonomy architectures are increasingly adopted to compensate for neural decoding variability in practical deployments.

Regarding **RQ2**, recent work shows a gradual shift from subject-dependent calibration toward cross-subject generalization strategies. Transfer learning, feature alignment, and lightweight adaptation mechanisms are emerging as promising approaches for reducing calibration overhead while maintaining reliable control performance.

For **RQ3**, evaluation practices across neural directional control studies remain heterogeneous. Differences in experimental protocols, latency reporting, and performance metrics limit direct comparison between systems. These findings highlight the importance of developing standardized benchmarking frameworks that incorporate both technical performance measures and human-centered usability indicators.

Overall, advancing EEG-based directional BCIs toward real-world deployment will require tighter integration between decoding algorithms, adaptive modeling, and human-centered evaluation. Establishing shared benchmarking practices and reproducible experimental pipelines represents an important step toward scalable and deployable neural control technologies.

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