

Multimodal Neural Signal Modeling for Personalized Neurorehabilitation Using Brain–Computer Interfaces and Reinforcement Learning

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Abstract

Personalized neurorehabilitation increasingly depends on computational systems that can interpret neural activity, infer evolving patient states, and adapt therapeutic assistance over time. Brain-computer interfaces provide a direct pathway for translating endogenous neural signals into control actions, while reinforcement learning offers a framework for sequential decision-making under uncertainty. When these approaches are combined with multimodal neural and behavioral modeling, they create opportunities for rehabilitation systems that are more responsive, patient-specific, and functionally meaningful than fixed protocol-driven devices. However, the integration of such systems raises substantial architectural, clinical, ethical, and infrastructural challenges. This paper examines multimodal neural signal modeling for personalized neurorehabilitation using brain-computer interfaces and reinforcement learning from a system-level perspective. It analyzes the structural trade-offs among signal fidelity, latency, autonomy, safety, and interpretability. It considers how reinforcement learning can support adaptive rehabilitation while remaining constrained by clinical governance, human oversight, and fairness requirements. The discussion further addresses deployment across hospitals, homes, and community settings, including issues of data infrastructure, maintenance, energy use, and long-term sustainability. It argues that personalized neurorehabilitation should be understood not merely as a decoding problem but as a socio-technical system requiring robust uncertainty management, transparent reward design, inclusive data practices, and policy frameworks that protect neural privacy and patient agency. The conclusion emphasizes that future progress depends on integrating signal processing, control theory, clinical expertise, and governance into a coherent, patient-centered architecture.

Keywords

brain-computer interfaces, neurorehabilitation, multimodal signal modeling, reinforcement learning, personalization, uncertainty, human-in-the-loop control, neural privacy, clinical deployment, socio-technical systems.

1. Introduction

Brain-computer interfaces have moved from laboratory demonstrations toward clinically meaningful applications in communication, motor restoration, and neurorehabilitation. Early systems established that neural activity can be decoded into control signals for cursors, prostheses, and spelling devices, thereby creating a foundation for assistive technologies that bypass damaged pathways [1], [2]. Subsequent work demonstrated that intracortical recordings can enable individuals with severe paralysis to control external devices with remarkable flexibility, while non-invasive approaches using electroencephalography have supported motor imagery training, neurofeedback, and rehabilitation after stroke [3], [4], [5]. These developments have encouraged the view that neurorehabilitation can become more personalized, data-driven, and adaptive when neural signals are interpreted continuously rather than intermittently.

At the same time, personalization in neurorehabilitation is not simply a matter of improving classifier accuracy. Rehabilitation involves longitudinal change, patient motivation, fatigue, compensation strategies, and variable clinical goals. A system that performs well in a single session may fail when the patient's neural signatures shift, medication changes, or the rehabilitation context moves from hospital to home. Multimodal neural signal modeling addresses this problem by combining electrophysiological, hemodynamic, kinematic, and behavioral information into a richer representation of the patient's state [6], [13]. Reinforcement learning adds a sequential decision-making layer that can adjust task difficulty, stimulation parameters, feedback timing, and assistance levels based on observed outcomes [7], [8]. Together, these approaches suggest a new class of neurorehabilitation systems that learn with the patient rather than merely classifying neural states.

Yet the integration of brain-computer interfaces and reinforcement learning also introduces structural risks. Reward functions may encode narrow clinical metrics that do not align with patient values. Learned policies may exploit neural artifacts or environmental shortcuts rather than promote genuine recovery. Multimodal data streams raise privacy and governance concerns because they can reveal cognitive, emotional, and motor states. Deployment across clinical and domestic infrastructures requires robust hardware, connectivity, maintenance, and support models that are often absent from research prototypes [17], [18]. This paper therefore adopts a system-level orientation, examining not only decoding performance but also architecture, governance, fairness, sustainability, and policy implications.

The central argument is that personalized neurorehabilitation using brain-computer interfaces and reinforcement learning should be designed as a human-in-the-loop socio-technical system. Personalization must be constrained by safety, interpretability, and clinical accountability. Reinforcement learning must be subordinate to therapeutic goals and patient agency rather than optimized solely for task success. Multimodal modeling must be accompanied by uncertainty-aware control, inclusive data practices, and transparent evaluation. By expanding the discussion beyond algorithmic novelty, this paper aims to clarify the trade-offs that determine whether such systems can be deployed responsibly and sustained over time.

2. Conceptual Foundations of Multimodal Neural Signal Modeling

Multimodal neural signal modeling begins from the premise that no single measurement captures the full complexity of rehabilitation-relevant brain and body states. Electroencephalography offers high temporal resolution and portability, making it attractive for repeated training and home use, but it is sensitive to artifacts and has limited spatial

specificity [1], [5]. Intracortical and electrocorticographic recordings provide higher signal quality and spatial precision, but they require surgical intervention and specialized maintenance [2], [3]. Functional near-infrared spectroscopy and functional magnetic resonance imaging provide complementary hemodynamic information, although their latency and physical constraints limit closed-loop rehabilitation applications. Kinematic sensors, electromyography, eye tracking, and behavioral logs add information about movement attempts, compensatory strategies, and engagement [6], [13]. A multimodal system seeks to fuse these streams to estimate latent states such as attention, fatigue, intention, and motor recovery.

The conceptual value of multimodality lies in complementarity and redundancy. Complementarity means that different modalities constrain different aspects of the patient's state. For example, electrophysiological signals may indicate attempted movement before overt behavior is observable, while kinematic sensors confirm whether the movement was executed. Redundancy means that if one modality degrades, others may preserve a usable estimate. In clinical neurorehabilitation, this redundancy is not merely technical convenience; it supports safety and trust. A system that relies exclusively on a noisy non-invasive signal may deliver inappropriate assistance or reinforce maladaptive patterns. A system that integrates behavioral evidence can detect such errors and adjust its intervention [10], [14].

Personalization requires more than subject-specific calibration. It involves modeling individual trajectories of recovery, preferences, and tolerances. Two patients with similar lesions may respond differently to feedback intensity, pacing, or task complexity. Multimodal data can support personalized models by capturing physiological arousal, cognitive load, and emotional response alongside motor performance. However, this raises a fundamental trade-off between model complexity and clinical interpretability. Highly flexible models may improve predictive accuracy while obscuring why a decision was made. In rehabilitation, where clinicians must explain and justify interventions, interpretability is not optional [16]. The design challenge is therefore to build multimodal representations that are rich enough for adaptation but structured enough for clinical oversight.

Another foundational issue is temporal scale. Neural signals fluctuate at millisecond scales, behavioral performance evolves over seconds, and recovery unfolds over weeks or months. Reinforcement learning can operate at multiple horizons, but the reward structure must reflect these nested timescales. Immediate rewards may encourage effort or engagement, while delayed rewards must capture functional gains. If the system optimizes only immediate task success, it may create dependency on assistance or discourage patients from attempting difficult movements. A multimodal model can help by distinguishing transient fluctuations from durable change, but it must be coupled with a control architecture that respects clinical time constants [7], [10], [15].

3. System Architecture and Integration Trade-Offs

A practical neurorehabilitation architecture typically includes sensing, preprocessing, representation learning, state estimation, policy selection, actuation, and clinical interface layers. The sensing layer acquires neural, physiological, and behavioral data. Preprocessing addresses artifacts, synchronization, and missing data. Representation learning transforms raw signals into features or embeddings. State estimation infers the patient's current condition and intent. Policy selection determines the rehabilitation action, such as adjusting task difficulty, providing sensory feedback, or triggering assistance. Actuation delivers the intervention through robotic devices, virtual environments, electrical stimulation, or auditory and visual

cues. The clinical interface allows therapists and patients to inspect, override, and personalize the system [2], [6], [13].

Each layer introduces trade-offs. Higher sampling rates and more modalities improve information content but increase bandwidth, computation, and power consumption. Low-latency control is essential for embodied rehabilitation, yet heavy multimodal fusion can introduce delays that disrupt the sense of agency. Cloud-based processing may enable advanced models and centralized updates, but it raises privacy risks and dependence on connectivity. Edge processing improves responsiveness and data locality, but it constrains model size and requires robust device management. A well-designed system may therefore use a hybrid architecture: time-critical decoding and safety checks occur locally, while slower personalization and population-level learning occur in governed, privacy-preserving infrastructure [15], [17].

Reinforcement learning adds another architectural layer. The policy must choose actions that are safe, clinically meaningful, and acceptable to the patient. This requires constraints that are not naturally expressed in a simple reward function. For instance, a policy might increase task difficulty to maximize engagement, but excessive difficulty can cause frustration or injury. A policy might reduce assistance to promote independence, but too little assistance can reinforce failure. These constraints suggest the need for shielding mechanisms, conservative action sets, and clinician-defined boundaries. The reinforcement learning component should be viewed as an adaptive advisor within a broader control system, not as an autonomous therapist [7], [8], [9].

Multimodal integration also raises synchronization and semantic alignment problems. Signals collected by different devices may have different clocks, noise profiles, and missingness patterns. Neural data may be recorded continuously, while behavioral ratings are entered sporadically by a therapist. Simply concatenating features can produce brittle models that confuse correlation with causation. More robust architectures use modality-specific encoders, attention mechanisms, and missing-data strategies. However, these methods increase complexity and can make validation difficult. In clinical translation, the architecture must support auditability: researchers and regulators need to know which modalities contributed to a decision and whether the system behaved consistently across patients and settings [13], [14], [16].

4. Reinforcement Learning for Adaptive Rehabilitation Control

Reinforcement learning provides a formal framework for learning sequential decisions from interaction. In neurorehabilitation, the agent could be the rehabilitation system, the environment could include the patient, the task, and the clinical setting, and the reward could reflect functional improvement, engagement, or adherence. Deep reinforcement learning has achieved strong results in domains with high-dimensional observations and delayed rewards, suggesting potential for complex rehabilitation tasks [7], [8], [9]. However, clinical rehabilitation differs from games and simulated control because the environment includes a human with changing physical and emotional states, ethical constraints, and long-term goals that cannot be fully specified in advance.

Reward design is therefore a central challenge. A narrow reward such as movement accuracy may encourage compensatory movements that undermine recovery. A reward based only on neural modulation may train patients to produce signals that satisfy the decoder but do not generalize to daily life. A reward based on session attendance may improve adherence but not

functional outcome. Effective reward design likely requires multi-objective formulations that balance immediate performance, movement quality, effort, safety, and patient-reported experience. Because these objectives may conflict, the system should expose trade-offs to clinicians and patients rather than hide them inside a single scalar value [10], [16].

Personalization in reinforcement learning can occur through patient-specific policies, meta-learning, or contextual bandits. Patient-specific policies adapt directly to one individual but may require substantial data. Meta-learning can initialize a policy from population data and fine-tune it for a new patient, potentially reducing calibration burden. Contextual methods can select interventions based on observed state without learning a fully general sequential policy. Each approach has implications for data governance and fairness. Population-trained models may encode biases from previous clinical trials, while purely individual models may be unstable when data are scarce. A hybrid strategy that combines population priors with strong individual adaptation and clinician oversight is more likely to be clinically acceptable [14], [15], [17].

Uncertainty is especially important in reinforcement learning for neurorehabilitation. Neural decoders are uncertain because signals are noisy and non-stationary. Policies are uncertain because the effect of an intervention on a patient is not fully known. If the system ignores uncertainty, it may take unsafe actions or overfit to transient states. If it becomes too conservative, it may fail to provide meaningful therapy. Recent work on probabilistic co-control in brain-computer interfaces treats uncertainty as a control signal rather than merely an error to be minimized, suggesting that uncertainty can be used to modulate the division of labor between the human and the machine [12]. In rehabilitation, this perspective is valuable because it supports shared control: when neural evidence is ambiguous, the system can defer to patient intent, request confirmation, or reduce assistance rather than making a confident but wrong decision.

5. Uncertainty, Robustness, and Human-in-the-Loop Co-Control

Human-in-the-loop co-control is essential for neurorehabilitation because the patient is not a passive environment. The patient learns, fatigues, strategizes, and may deliberately change behavior. A reinforcement learning system that treats the patient as a fixed environment will misestimate the effects of its actions. Co-control frameworks distribute authority between the patient and the system, allowing each to compensate for the other's limitations. The patient can provide high-level goals, corrective signals, or veto decisions, while the system can offer assistance, feedback, and consistency. Uncertainty-aware co-control makes this distribution dynamic. When neural decoding is confident, the system may grant more control to the user or provide nuanced assistance. When uncertainty is high, the system may shift to safer modes, such as passive support or prompts for explicit confirmation [12], [16].

Robustness must be evaluated across multiple dimensions. Signal robustness concerns noise, electrode displacement, and changes in neural tuning. Policy robustness concerns generalization across tasks, sessions, and patients. Clinical robustness concerns safety under fatigue, pain, medication changes, and comorbidities. Social robustness concerns whether the system works for patients with different languages, education levels, and technology access. A system that is robust only in controlled laboratory conditions is insufficient for rehabilitation, where environments are messy and support varies. Robustness testing should therefore include adversarial scenarios, missing modalities, connectivity loss, and human error. It should also include the ability of clinicians to detect and recover from failures [14], [17].

Interpretability and transparency are closely related to robustness. If a policy changes assistance without explanation, patients may lose trust or agency. If a decoder fails, clinicians need to understand whether the failure arose from signal artifacts, model uncertainty, or interface design. Explainable artificial intelligence can provide useful summaries, but explanations must be meaningful to clinical users rather than only to machine learning engineers. In high-stakes rehabilitation, interpretable models or constrained architectures may sometimes be preferable to more accurate but opaque alternatives [16]. Transparency also supports accountability: when an adverse event occurs, regulators and ethics boards need a record of system states, decisions, and human overrides.

Fairness in co-control requires attention to who benefits and who bears risk. Patients with severe motor impairment may have less ability to correct a faulty system, making safety mechanisms more important. Patients with cognitive or communication differences may need alternative confirmation modalities. If training data overrepresent certain lesion types, ages, or cultural contexts, the system may perform unevenly. Fairness is not achieved by ignoring group differences; it requires evaluating performance across subgroups and designing interfaces that accommodate diverse needs. It also requires inclusive governance, so that patients and caregivers have a voice in how personalization and automation are implemented [17], [18], [19].

6. Governance, Fairness, Privacy, and Policy

Neurorehabilitation systems that combine brain-computer interfaces with reinforcement learning raise governance questions that extend beyond device regulation. Neural data can reveal information about attention, emotion, intention, and cognitive state. When combined with behavioral and clinical data, they create a detailed longitudinal profile of a person's recovery and daily life. This profile may be valuable for treatment, but it is also vulnerable to misuse by insurers, employers, or commercial platforms. Privacy protection must therefore include data minimization, purpose limitation, secure storage, and patient-controlled sharing. It must also address inferences: even if raw neural data are protected, derived states and predictions may be sensitive [17], [20].

Policy frameworks for artificial intelligence in health care emphasize transparency, accountability, fairness, and human oversight [17], [18], [19]. These principles are relevant, but they are not self-executing. In neurorehabilitation, governance must specify who is responsible when an adaptive system makes a harmful recommendation. Is it the clinician, the manufacturer, the hospital, or the algorithm developer? Regulatory pathways must accommodate learning systems that change over time, potentially requiring post-market surveillance, version control, and continuous safety monitoring. Clinical governance must also define appropriate use: which patients are eligible, what data are required, and when human supervision is mandatory. Without such specifications, personalization can become a source of inconsistency rather than quality improvement.

Fairness requires more than non-discrimination statements. It requires representative data collection, subgroup performance reporting, and attention to access. Brain-computer interface rehabilitation may be expensive, requiring specialized hardware, trained staff, and reliable internet. If deployment is limited to well-resourced centers, it may widen existing rehabilitation disparities. Policy should therefore consider reimbursement models, public procurement, and infrastructure investment. It should also support interoperability so that patients can move between clinical, home, and community settings without losing their

therapeutic history. Governance must balance innovation with equity, ensuring that adaptive systems do not become privileges available only to those who can afford them [17], [19], [20].

Patient agency is a central ethical concern. Reinforcement learning can shape behavior through rewards, prompts, and feedback. If the system is optimized for adherence or task performance, it may unintentionally pressure patients in ways that conflict with their values. Informed consent for adaptive neurorehabilitation should therefore be ongoing rather than one-time. Patients should be able to inspect their data, understand how personalization works, and withdraw or adjust automation. Caregivers and clinicians should be involved in goal setting. Governance should protect against coercive use, especially in contexts where patients feel dependent on a device for communication or mobility. These concerns link neurorehabilitation to broader debates about neurorights and the boundaries of cognitive liberty [20].

7. Deployment, Infrastructure, and Sustainability

Deployment of multimodal neurorehabilitation systems involves more than installing a device. It requires an ecosystem of sensors, computing resources, network connectivity, clinical workflows, and technical support. In hospital settings, systems must integrate with electronic health records, comply with sterilization and safety requirements, and fit within therapist schedules. In home settings, they must be usable by patients and caregivers with varying technical confidence. In community settings, they must function across different environments and support continuity of care. Each setting imposes different constraints on latency, bandwidth, power, and privacy. A system designed only for the laboratory may fail when confronted with these realities [6], [15].

Infrastructure choices have long-term sustainability implications. Cloud-based reinforcement learning can centralize updates and leverage large datasets, but it consumes energy and depends on continuous connectivity. Edge computing reduces data transmission and improves responsiveness, but it may require frequent hardware upgrades. Battery-powered wearable sensors improve mobility but introduce charging and maintenance burdens. Surgical implants offer high signal quality but require specialized follow-up and may have limited lifespans. Sustainable design must consider total cost of ownership, repairability, interoperability, and environmental impact. It must also plan for obsolescence: if a manufacturer discontinues support, patients should not lose access to essential rehabilitation functions [2], [17].

Maintenance and human infrastructure are often underestimated. Multimodal systems require calibration, troubleshooting, and software updates. Clinicians need training to interpret system outputs and manage overrides. Patients and caregivers need accessible documentation and responsive support. If these elements are absent, the system may be abandoned even if it performs well in trials. Deployment should therefore include workflow analysis, usability testing, and long-term service models. It should also include contingency plans for connectivity loss, sensor failure, and cyberattacks. Security is not only a privacy issue; compromised rehabilitation systems could cause physical harm or undermine trust [17], [18].

Sustainability also concerns clinical integration. A personalized reinforcement learning system may generate recommendations that conflict with established therapeutic practices. Clinicians may resist if the system is opaque or if it increases documentation burden. Successful deployment requires participatory design, where therapists help define goals, constraints, and interaction patterns. It also requires evidence that the system improves outcomes or reduces burden compared with standard care. Pilot studies should measure not

only performance but also workflow fit, patient acceptance, and cost. Without such evidence, adaptive neurorehabilitation may remain a promising but marginal technology [10], [13], [16].

8. Evaluation and Clinical Translation

Evaluation of multimodal neurorehabilitation systems must move beyond decoding accuracy and task success. Clinical translation requires evidence across multiple levels: technical validity, clinical efficacy, patient-reported outcomes, safety, equity, and economic viability. Technical validation should assess signal quality, robustness to artifacts, latency, and generalization across sessions. Clinical validation should assess functional improvement, transfer to daily activities, and maintenance of gains. Patient-centered validation should assess motivation, agency, fatigue, and quality of life. Equity validation should assess performance across demographic and clinical subgroups. Economic validation should consider costs of devices, training, support, and infrastructure [3], [10], [11].

Randomized controlled trials remain important, but they may be poorly suited to adaptive systems that change over time. Alternative designs such as sequential multiple assignment randomized trials, n-of-one studies, and hybrid effectiveness-implementation designs can provide more nuanced evidence. These designs can evaluate which components of personalization matter, how much human oversight is needed, and when automation improves or harms outcomes. They can also detect interactions between patient characteristics and system behavior. Because reinforcement learning policies may evolve, trial protocols must specify version control, update rules, and stopping criteria. Regulators will need mechanisms to review changes without requiring a completely new trial for every model update [15], [17].

Safety evaluation should include both physical and psychological harms. Physical harms may arise from inappropriate assistance, excessive repetition, or device malfunction. Psychological harms may include frustration, loss of agency, dependency, or privacy violations. Multimodal systems can detect some of these states, but detection should not replace clinical judgment. Safety protocols should define thresholds for stopping a session, escalating to a clinician, or reverting to a conservative mode. They should also include transparent logging so that adverse events can be reconstructed. In reinforcement learning, safety can be improved through constrained action spaces, conservative policies, and human veto, but these measures must be tested rather than assumed [7], [12], [16].

Translation also requires attention to training and workforce development. Clinicians, therapists, and technicians need interdisciplinary literacy in neural signal processing, machine learning, and human factors. Patients and caregivers need understandable explanations of what the system does and does not do. Educational materials should avoid overpromising recovery or implying that the device replaces human care. Interdisciplinary teams should include ethicists, legal experts, and patient advocates from the beginning, not as afterthoughts. The complexity of multimodal reinforcement learning systems makes participatory governance a practical necessity, not merely a normative ideal [18], [19], [20].

9. Future Directions and Cross-Domain Lessons

Future research should pursue architectures that are modular, uncertainty-aware, and clinically governable. Modularity allows components to be updated or replaced without redesigning the entire system. Uncertainty-aware control allows the system to shift between autonomy and assistance as conditions change. Clinical governability ensures that therapists can understand, constrain, and override system behavior. These properties are more important

than achieving marginal gains in decoding accuracy. They also support regulatory review because they make system behavior more predictable and auditable [12], [14], [16].

Cross-domain lessons from autonomous systems, robotics, and human-computer interaction can inform neurorehabilitation. In aviation and industrial automation, shared control and mode awareness are critical for safety. In robotics, reinforcement learning has benefited from simulation, safety constraints, and human demonstrations. In recommender systems, personalization has revealed the risks of feedback loops and filter bubbles. Neurorehabilitation should learn from these domains without treating patients as ordinary users. The stakes are higher, the data are more sensitive, and the goals are deeply personal. Personalization must therefore be evaluated not only by engagement but by meaningful recovery and patient-defined well-being [8], [9], [15].

Another promising direction is federated and privacy-preserving learning. Instead of centralizing sensitive neural data, models can be trained across institutions while keeping data local. This approach can improve generalization and fairness while respecting privacy, but it introduces challenges in communication, heterogeneity, and governance. Federated systems require common data schemas, secure aggregation, and clear rules for model ownership. They also require attention to equity: institutions with fewer resources may struggle to participate. If designed well, federated learning could support a learning health system for neurorehabilitation while preserving patient control [17], [18].

Finally, future systems should support lifelong personalization. Recovery does not end after a clinical trial, and neural signals may change with aging, medication, or disease progression. A system that works for months may need to adapt for years. Lifelong learning raises risks of drift, catastrophic forgetting, and unintended policy changes. It requires periodic recalibration, clinician review, and patient consent. It also requires sustainable data stewardship so that patients can benefit from accumulated personalization without becoming locked into a proprietary ecosystem. These challenges suggest that the most important innovations may be institutional and architectural rather than purely algorithmic [10], [12], [20].

10. Conclusion

Multimodal neural signal modeling for personalized neurorehabilitation using brain-computer interfaces and reinforcement learning represents a powerful but demanding research direction. It promises systems that can interpret diverse neural and behavioral signals, adapt to individual recovery trajectories, and provide assistance that evolves with the patient. Realizing this promise requires more than improved decoders or more sophisticated reinforcement learning algorithms. It requires careful system architecture, uncertainty-aware co-control, transparent reward design, robust deployment infrastructure, and governance that protects privacy, fairness, and patient agency. The integration of neural interfaces with adaptive learning also raises questions about accountability, equity, and long-term sustainability that cannot be resolved by technical performance alone.

A responsible path forward treats personalization as a collaborative process among patients, clinicians, engineers, and policymakers. Reinforcement learning should operate within clinical constraints and remain subordinate to human goals. Multimodal data should be used to enrich understanding while respecting privacy and minimizing harm. Deployment should be planned for maintenance, interoperability, and equitable access, not only for initial efficacy. Evaluation should include functional, psychological, ethical, and economic outcomes. If these dimensions are addressed together, personalized neurorehabilitation can become a meaningful

advance in care rather than a fragile technological demonstration. The future of brain-computer interface rehabilitation depends on building systems that are not only intelligent but also trustworthy, inclusive, and sustainable.

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