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Narrative Review

From Lab to Clinic: A Narrative Review of Motor Imagery Brain-Computer Interfaces for Neurorehabilitation in India

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ABSTRACT

Background: Non-invasive electroencephalography (EEG)-based motor imagery brain-computer interfaces (MI-BCIs) offer promising neurorehabilitation pathways by decoding imagined movements to drive assistive rehabilitation devices. However, translating these systems from controlled laboratories into active clinical workflows remains a significant hurdle.

Objective: This narrative review examines the socio-technical, computational, and practical challenges of deploying MI-BCIs for clinical rehabilitation, with a specific focus on the fragmented, high-throughput healthcare sector in India.

Review Methodology: A structured search was conducted across international and national databases—including PubMed, Scopus, Google Scholar, and the Clinical Trials Registry - India (CTRI)—identifying 15 key studies published between 2012 and 2026 focusing on human-machine co-adaptation, user training standardization, and real-world BCI usability.

Conclusion: By synthesizing advanced computational methods—such as real-time adaptive classifiers and Markov chain-based user assessments—with ground-level clinical workflows, this review outlines a four-stage co-adaptive translational blueprint. We advocate for a paradigm shift from pure algorithmic decoding accuracy to holistic, patient-centered usability, establishing a sustainable framework for scalable clinical neurorehabilitation in emerging economies.

Keywords: Brain-Computer Interface (BCI), clinical translation, co-adaptive learning, data privacy, motor imagery, narrative review, neurorehabilitation, non-responders.

INTRODUCTION

Non-invasive brain-computer interface (BCI) systems, particularly those utilizing electroencephalography (EEG) to decode active motor imagery (MI), represent a promising technological intervention for clinical neurorehabilitation. By mapping the kinesthetic imagination of limb movement to external mechanical devices (such as robotic orthoses or functional electrical stimulation [FES] systems), MI-BCIs support active neuroplasticity and functional motor recovery in survivors of stroke, spinal cord injuries, and traumatic brain injuries. However, as neurotechnology transitions from controlled laboratory-scale prototypes into active clinical workflows, researchers and clinicians encounter a significant translational gap. Historically, the academic literature has disproportionately prioritized overcoming isolated algorithmic limits such as spatial filtering, feature extraction, and mathematical classification optimization within highly controlled, noise-free, and homogeneous environments [1,2]. Yet, in real-world clinical settings, BCI performance relies on a highly dynamic socio-technical system where technological hardware, software algorithms, clinical operators, and heterogeneous patient populations interact in real time. To achieve genuine clinical viability, the primary focus of BCI

design must shift from static decoding accuracy toward co-adaptive, subject-centered learning models. This co-adaptive philosophy recognizes that optimal controllability is a bidirectional process: the machine's decoding algorithms must continuously adapt to the non-stationary, session-to-session drift of the user's EEG signals, while the user simultaneously learns to modulate their sensorimotor rhythms (SMR) through active, contingent feedback [3,4]. This dual-challenge is particularly pronounced in emerging healthcare markets, such as India, where advanced medical devices must navigate severe structural constraints, high clinical throughput, and cultural-linguistic heterogeneity. This narrative review examines the socio-technical factors that govern clinical BCI adoption, specifically focusing on the operational adaptation of hardware, linguistic mediation of cognitive training instructions, and standard clinical data privacy guidelines. To systematically address the translational bottleneck, this narrative review investigates three explicit research questions:

1. What technical and physiological factors limit the translation of motor imagery BCIs from laboratory settings to real-world clinical environments?
2. How do human psychophysiological factors, including cognitive workload, fatigue, and motivation, influence sustained BCI control during rehabilitation?

3. What India-specific infrastructural, linguistic, and regulatory considerations must be integrated into the deployment strategies of multinational neurotechnology subsidiaries to ensure ethical and sustainable adoption?

REVIEW METHODOLOGY:

To provide a rigorous, evidence-based critique, a structured narrative review of the literature was conducted. The review targeted studies addressing non-invasive EEG-based motor imagery, BCI clinical translation, co-adaptive human-machine learning, and assistive device integration in emerging healthcare sectors. The search was performed across three primary electronic databases: PubMed, Scopus, and Google Scholar and supplemented by India-specific portals: the Clinical Trials Registry - India (CTRI) to assess registered clinical BCI trials, and the Shodhganga repository to review relevant doctoral theses within Indian academic institutions. The search covered publications from January 2012 through August 2026. The search strategy utilized combinations of Boolean operators and the following keyword strings: ('Motor Imagery BCI' OR 'SMR-BCI') AND ('clinical translation' OR 'rehabilitation' OR 'usability') AND ('co-adaptation' OR 'user training') AND ('India' OR 'emerging healthcare' OR 'low-resource'). Articles were evaluated based on the inclusion criteria: (a) published in English in peer-

reviewed journals, academic conferences, or established preprint repositories (e.g., bioRxiv, explicitly treated as a preprint in this review); (b) focused on motor imagery or sensorimotor rhythm-based EEG control; and (c) addressed clinical adoption, user experience, or multi-session user training. Articles that focused exclusively on offline algorithm optimization with no discussion of online performance, human user factors, or translation were excluded. A total of 15 key publications and clinical registry entries were selected and synthesized to form the basis of this narrative review.

TECHNICAL TRANSLATIONAL BARRIERS & EVIDENCE :

A primary hurdle in scaling MI-BCI technologies commercially is the historical terminology and conceptualization of user performance. The literature has frequently utilized the term 'BCI illiteracy' to describe individuals who cannot readily generate detectable sensorimotor rhythms (SMR) for BCI control. However, this term has faced substantial academic criticism because it implies an inherent physiological or cognitive deficiency within the user. In clinical practice, poor performance is more accurately conceptualized as a failure of the broader socio-technical interface including

inadequate training protocols, complex instructions, sub-optimal electrode placement, and static, non-adaptive decoding algorithms. Therefore, current research advocates for the neutral term 'BCI non-responders' or 'low-performing users,' emphasizing that usability is a shared, system-level responsibility. Furthermore, quantitative claims regarding BCI usability require careful context. For instance, the widely cited estimate that 15% to 30% of users are non-responders is highly dependent on the target population, the specific mental tasks used, the electrode layout, and the classification algorithm. Similarly, the common laboratory accuracy drop during real-time, closed-loop trials where offline training accuracies of ~80% frequently decline to ~70% during active online control is not a universal standard [5]. This drop is highly modulated by physiological factors like signal non-stationarity and user cognitive fatigue, as well as computational factors such as the classifier's robustness to session-to-session drift. Describing a ~70% decoding accuracy as an operational usability threshold must be justified clinical-by-clinical: for basic binary control (such as driving a wheelchair forward/backward), a 70% threshold is functional, whereas for multi-class control, higher accuracies or robust error-correction layers are mandatory.

EEG HARDWARE INTERFACE TRADE-OFFS:

To achieve scalability under high patient throughput, clinical operators must balance the trade-offs of the EEG physical interface. High-density wet EEG systems remain the standard for high-fidelity research, but sparse, dry, plug-and-play sensors are emerging as candidates for routine clinical practice. Table 1 presents a balanced, evidence-based comparison of these hardware configurations, highlighting that dry EEG is not an automatic superior solution but presents distinct operational trade-offs.

HUMAN FACTORS & CLINICAL USABILITY:

A central determinant of clinical BCI success is the psychological and cognitive status of the user. Active motor imagery requires intense concentration, creating a substantial cognitive workload that elevates patient mental demand, physical effort, and fatigue across consecutive training sessions [6]. Sustained high cognitive workload leads to user frustration, particularly when signal non-stationarity causes the decoding algorithm to fail. If a system requires tedious, repetitive mental commands without immediate, motivating feedback, user engagement collapses, directly halting neuroplastic changes. Standardizing user-centered training environments with real-time, personalized feedback loops is critical to boosting motivation and mitigating cognitive fatigue [7,8]. To transition BCI from a laboratory curiosity to a clinical standard, the

evaluation framework must expand beyond offline classification accuracy. Relying solely on percent-correct metrics fails to capture a device's actual functional utility. Researchers must integrate alternative, human-centered metrics, including: (a) Information Transfer Rate (ITR) to evaluate speed and accuracy, (b) task completion rate and false activation rate to assess operational safety, (c) calibration duration and session stability to determine clinical setup efficiency, and (d) standardized usability scales (such as the System Usability Scale, SUS), NASA-TLX for cognitive workload, and patient-reported outcome measures (PROMs) to track long-term adherence. Most importantly, researchers must distinguish BCI decoding performance from the downstream outcomes of functional motor training, neuroplastic reorganization, and durable clinical recovery. These dimensions are not equivalent; a patient can exhibit excellent neuroplastic rehabilitation gains even if online BCI classification accuracy remains moderate.

INDIA-SPECIFIC SOCIO TECHNICAL CHALLENGES : Deploying sophisticated neurotechnologies within the Indian clinical context requires a deep understanding of the local healthcare ecosystem. The major hurdles are not merely technical, but reside in the unique intersections of local medical infrastructures, linguistic diversity.

Factor	High-Density Wet EEG	Sparse/Dry EEG
Signal Quality	Generally strong and robust; high signal-to-noise ratio.	Variable; more susceptible to environmental & motion noise.
Setup Time	Longer (20-40 mins); requires skin prep and conductive gel.	Shorter (2-5 mins); dry electrodes require no gel skin prep.
Patient Comfort	Good initially; gel requires washing and causes irritation.	Potentially better; avoids messy hair cleanup, but rigid pins pinch.
Maintenance	Higher; electrodes must be washed and sterilized thoroughly.	Lower; dry sensors can be quickly disinfected between uses.
Portability	Limited; typically tied to desktop amplifiers and carts.	Better; highly portable, often wireless and battery-operated.
Motion Robust	Excellent due to gel buffering and secure caps.	Potential challenge; slide and movement of pins cause artifacts.
Capital Cost	Potentially higher; research grade equipment.	Potentially lower; mass-produced commercial or sparse setups.

Table 1. Key Differences Between Controlled BCI Research and Clinical Deployment

**BCI AND CLINICAL
NEUROREHABILITATION RESEARCH IN**

INDIA: The current landscape of clinical neurorehabilitation in India is highly fragmented, characterized by a sharp divide between premium private healthcare chains and heavily overburdened public tertiary teaching hospitals. Premier academic institutions, such as the National Institute of Mental Health and Neurosciences (NIMHANS), Bangalore, and the All India Institute of Medical Sciences (AIIMS), New Delhi, have spearheaded initial BCI pilot studies and neurophysiological research. However, translating these academic pilots into widespread clinical practice is restricted by the absolute physical limitations of Indian medical infrastructure. Public rehabilitation centers face high patient-to-therapist ratios, where a single therapist may oversee dozens of patients daily. Consequently, the traditional laboratory-based BCI workflow, requiring lengthy prep and dedicated clean rooms, is operationally impossible. To be adopted, BCI systems must adapt to high-throughput settings, requiring robust plug-and-play hardware and intuitive, automated clinical software

**LINGUISTIC AND CULTURAL
ADAPTATION OF MOTOR IMAGERY
INSTRUCTIONS :** A highly localized and unexamined bottleneck is the linguistic and cultural mediation of motor imagery training instructions.

Standardized MI protocols are engineered in English-centric Western labs, utilizing abstract conceptual terminology. For example, instructions requiring a patient to 'imagine a first-person, kinesthetic sensation of right-hand grasping' are cognitively foreign and difficult to understand for patients from diverse educational or low-literacy backgrounds.

In India's multilingual environment, therapists must translate these instructions into highly distinct regional languages (such as Hindi, Kannada, Tamil, or Bengali).

Currently, there is no standardized protocol for these translations, and poor instruction mediation leads to weak or inconsistent sensorimotor rhythm modulation. Rather than presenting this as a speculative limitation, the linguistic and cultural adaptation of motor-imagery instructions represents a testable translational research question in multilingual healthcare environments.

Future empirical trials must evaluate whether standardizing instructions using culturally familiar, localized analogies and metaphors (e.g., imagining holding a specific local object or performing a familiar physical task) significantly improves EEG pattern distinctiveness and online decoding performance.

CLINICAL DATA SECURITY AND PRIVACY

GUIDELINES: Evolving clinical data standards and patient privacy guidelines represent an important consideration for deploying neurotechnology in India. As advanced BCI systems increasingly integrate into active clinical treatment, keeping patient neural data secure is paramount. Continuous brainwave (EEG) recordings are highly personal biometric signals that must be handled with care. While global trends move toward using secure, cloud-based setups for processing complex brain signals and monitoring patient state [9], clinical centers in India must ensure this data transmission remains safe, confidential, and in line with general clinical privacy standards. This involves simple, direct practices such as obtaining clear informed consent from patients, storing neural files in secure local clinical databases, and ensuring data transfer remains encrypted. By taking these straightforward steps to protect patient confidentiality, clinical facilities and technology providers can easily navigate privacy concerns while maintaining focus on patient recovery.

PROPOSED TRANSLATIONAL FRAMEWORK :

To bridge the gap between laboratory accuracy and real-world clinical effectiveness, we propose a comprehensive, four-stage socio-technical

translation framework. This blueprint addresses both the computational co-adaptation of machine learning algorithms and the systematic management of human psychophysiological states.

1. Calibration with Active Engagement: The initial phase establishes a robust individual baseline. Unlike passive, static calibration, the system utilizes active user-engagement paradigms with real-time visual feedback to maintain focus. Patient imagery vividness is pre-assessed using validated psychological scales (such as the KVIQ), allowing therapists to customize the visual feedback or select specific, highly discriminative motor imagery tasks (such as hand-grasping vs. foot-tapping) before signal acquisition.
2. Adaptive Online Control: During active trial operation, the system employs real-time adaptive Linear Discriminant Analysis (LDA) classifiers that continuously update parameters based on incoming EEG data [10]. This on-the-fly parameter update handles signal non-stationarity and session-to-session drift, significantly shortening training times and mitigating user frustration when control degrades.
3. Bidirectional Co-adaptation: Optimal control relies on a closed loop where machine and human learn in tandem. While the adaptive classifier tracks shifting feature spaces, the user's sensorimotor rhythm is actively shaped by machine feedback [11]. The system monitors user cognitive workload and fatigue through continuous theta/alpha ratio analysis. If fatigue crosses

a personalized threshold, the system automatically adjusts the feedback difficulty or triggers a therapeutic pause, managing user frustration and preventing performance drops.

4. Longitudinal Functional Tracking: The ultimate stage transitions from offline accuracy percentages to tracking durable, real-world clinical outcomes. BCI-enabled motor training is integrated with physical neuroprosthetics, robotic orthoses, or functional electrical stimulation (FES) to drive cortical reorganization [12]. Functional recovery is documented using standardized clinical scales (such as the Fugl-Meyer Assessment and Action Research Arm Test), while system adherence and adverse events including localized skin irritation or cognitive headaches are rigorously recorded.

EXPLAINING THE MARKOV CHAIN-BASED USER ASSESSMENT:

To support co-adaptive learning, the framework integrates a Markov chain-based user assessment method [13-17]. Traditional longitudinal metrics typically collapse high-dimensional, time-varying brain dynamics into static, overall accuracy averages. This static modeling fails to capture the subtle, trial-by-trial evolution of a user's neurophysiological performance. A Markov modeling approach maps BCI operation as a sequence of distinct, time-evolving states—for

instance, S0 (Resting baseline), S1 (Active motor imagery initiation), S2 (Sustained motor rhythm modulation), and S3 (Signal drift or cognitive distraction). By analyzing the transition probabilities between these states, clinical operators can mathematically model precisely when a low-performing user begins to lose control of the interface. This provides two key clinical utilities: (a) it identifies whether poor performance stems from an inability to initiate imagery (S0 to S1 block) or a failure to maintain sustained focus (rapid S2 to S3 transition), allowing therapists to personalize training; and (b) it provides a mathematical, interpretable predictor of user fatigue, triggering adaptive recalibration before performance drops, thereby presenting a superior alternative to static accuracy tracking.

CONCLUSION:

To advance non-invasive neurotechnology from controlled laboratories to unconstrained clinical practices, future research must prioritize: (a) large-scale, multisite clinical trials utilizing diverse, heterogeneous patient cohorts rather than small, selective samples of healthy university students; (b) the standardization of mu and beta frequency band definitions, referencing protocols, and calibration methodologies across different BCI platforms; and

(c) the empirical evaluation of localized, culturally mediated cognitive instructions in multilingual markets. The integration of passive brain-computer interfaces (pBCIs) to continuously monitor workload and stress must also be carefully aligned with clinical safety and data privacy guidelines to protect patient confidentiality.

In conclusion, as synthesized in this narrative review, the true maturity of clinical neurotechnology is measured not by how accurately we decode signals in a laboratory, but by how effectively we empower the patient in their natural environment.

Transitioning motor imagery BCIs from laboratory prototypes to practical, deployable technologies requires a paradigm shift from pure algorithmic accuracy to holistic clinical accessibility, human-centered design, and socio-technical adaptability.

By leveraging its growing clinical research centers and robust IT expertise, India has the potential to contribute substantially to the development of scalable, context-sensitive models of BCI-enabled neurorehabilitation, ensuring that advanced neurotechnological innovations successfully bridge the last mile to clinical utility.

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KP, SS: Conceptualization, methodology, formal analysis, investigation, resources, writing—original draft preparation, writing—review and editing, visualization, supervision, and project administration. All authors contributed to the review and editing of the manuscript and approved the final version.

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