

Brain Computer Interface: A Review of EEG Decoding Adaptive Rehabilitation and Edge AI

Dhome Pranav Pradip¹, Prof. Bangar Abhishek Popat², Prof. Bhosale Sachin Bajirao³

Research Scholar¹, Professor^{2,3}

Dept. of Computer Engineering^{1,2,3}
Jaihind College of Engineering, Pune, India

Abstract- Brain-computer interfaces establish a communication pathway between neural activity and external devices, offering opportunities for assistive interaction, motor rehabilitation, and cognitive-state monitoring. Despite advances in electroencephalography and artificial intelligence, practical deployment remains limited by noisy signals, variation across users, calibration burden, computational constraints, and uneven clinical evidence. This review examines five publications from 2023 to 2026 that address complementary aspects of these challenges: adaptive rehabilitation after stroke, tactile stimulation for cross-subject motor-imagery calibration, convolutional Transformer-based EEG decoding, embedded Edge AI systems, and clinical translation. A structured narrative synthesis is used to compare study objectives, methods, evaluation settings, findings, and limitations. The reviewed evidence suggests that adaptive feedback can support participation by users with poor initial BCI control, while tactile calibration may reduce dependence on demanding imagery tasks. Hierarchical temporal feature learning improves performance on selected cognitive classification benchmarks, but benchmark accuracy does not establish rehabilitation efficacy or reliable operation in everyday environments. Edge deployment introduces additional requirements for energy efficiency, latency, memory use, and data protection. Based on these findings, a conceptual seven-stage EEG architecture is proposed to connect signal-quality assessment, individualized calibration, efficient decoding, confidence-aware feedback, and monitored adaptation. The architecture is not experimentally validated. Future work should prioritize independent participant evaluation, prospective online studies, clinically meaningful outcomes, and transparent reporting of the trade-offs between accuracy, usability, and hardware efficiency.

Keywords— Brain-computer interface, Electroencephalography, Motor imagery, Transfer learning, Edge artificial intelligence, Neurorehabilitation

I. INTRODUCTION

A brain-computer interface (BCI) measures brain activity and converts selected signal patterns into outputs for a computer, communication aid, or other external system. Unlike conventional interfaces, a BCI can provide an interaction pathway without relying on the usual muscular output. Its usefulness depends on whether the detected neural information supports a meaningful task and whether feedback is timely enough for the user to understand and influence system behaviour [4], [5].

BCIs can be distinguished by their recording modality and intended function. Invasive approaches record through implanted interfaces,

whereas non-invasive approaches acquire signals without implantation. This review concentrates on electroencephalography (EEG), which is prominent in the selected papers because it supports portable acquisition and relatively accessible experimentation. EEG nevertheless remains vulnerable to eye movements, muscle activity, electrode-contact changes, and variation between recording sessions [4], [5].

Motor-imagery (MI) interfaces analyse activity associated with imagining a movement. Event-related desynchronization (ERD) in sensorimotor rhythms can provide a useful representation of this process. However, users differ in their ability to produce stable imagery-related signals. Repeated calibration can therefore be tiring and may exclude people who could otherwise benefit from assistive or rehabilitative applications [1], [2].

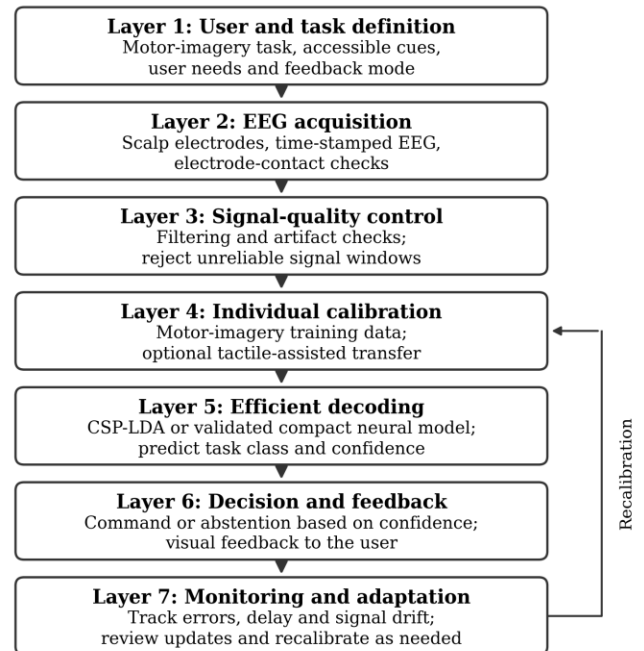
Other EEG tasks, such as attention and workload classification, address cognitive-state monitoring and must be evaluated separately from intentional movement control [3].

The central question of this review is how advances in calibration, decoding, adaptive feedback, and embedded processing can be combined into a practical EEG-based BCI. The five selected publications contribute evidence at different levels: a rehabilitation intervention, an offline calibration experiment, a decoding benchmark study, an engineering survey, and a clinical narrative review. Their findings are complementary, but they cannot be combined into a single accuracy ranking or a pooled estimate of treatment benefit.

A useful distinction is between active control and passive monitoring. In active control, the user intentionally produces a neural pattern to issue a command, as in motor imagery. Passive monitoring estimates a state such as fatigue or workload without requiring a deliberate command. Stimulus-driven paradigms, including P300 and steady-state visual evoked potentials, provide another route to interaction. These approaches have different attention, sensory, and training requirements; choosing a paradigm should therefore begin with the intended task and the user's capabilities rather than the classifier alone [5], [6], [10].

II. BCI SYSTEM ARCHITECTURE

The EEG-based brain-computer interface considered in this review is organized as a closed-loop system connecting the user, signal acquisition, signal processing, decoding, and feedback. The architecture below summarizes the seven stages developed in Section V. It is a conceptual synthesis of the reviewed work, not an experimentally validated integrated system. Its initial application is motor-imagery control, with adaptive rehabilitation and portable edge processing as design considerations [1], [2], [4].



BCI system architecture: seven processing layers with a recalibration loop (conceptual; not experimentally validated).

EEG acquisition captures the user's task-related signals. Signal-quality control filters recordings and rejects unreliable windows. Individual calibration, optionally supported by tactile stimulation, supplies training data for CSP-LDA or a validated compact neural decoder. Confidence-aware decisions produce a command or abstention, followed by user feedback. Monitoring tracks errors, latency, and drift to inform recalibration. Edge deployment requires measurements of memory, energy, and end-to-end delay [2], [4].

III. SELECTED LITERATURE

Adaptive BCI for motor recovery after stroke

Zhang et al. [1] investigated an adaptive BCI combined with functional electrical stimulation (FES) for upper-limb rehabilitation. The study included 33 subacute stroke patients, with 17 in the BCI group and 16 in the control group. The intervention used motor imagery, visual feedback, and performance-dependent assistance. FES was

triggered after completion of the imagery task, linking the patient's participation to subsequent movement-related feedback.

The reported improvement in the Fugl-Meyer Upper Extremity score was 9.8 ± 5.3 points in the BCI group and 4.3 ± 3.3 points in the control group, with a between-group p value of 0.003. Eleven of 17 BCI participants and four of 16 control participants reached the study's threshold for a clinically important difference. Improvements were retained at the six-month assessment among participants followed up; five participants were lost to follow-up [1]. These are clinical outcome measures, not EEG classification accuracies.

A significant contribution is the attention to patients with initially poor BCI performance. The study reported no significant difference in rehabilitative improvement between its low- and high-performance subgroups. This supports further investigation of adaptive assistance, but a non-significant subgroup comparison does not establish equivalence. The modest sample size, restriction to subacute stroke, and intensive schedule of approximately 18 one-hour sessions limit broader generalization [1].

The rehabilitation study also illustrates why feedback design is part of the intervention itself. Visual feedback allows a participant to observe progress during imagery, while movement-related feedback links task completion to a physical consequence. An adaptive controller can change the assistance provided when performance is poor.

However, evaluation must distinguish improved participation from improved independent neural control. Recording both assistance level and functional outcomes would help explain whether a participant is learning more effective control, receiving more support, or benefiting through a combination of the two [1].

Cross-subject calibration using tactile ERD

Zhong et al. [2] examined whether tactile stimulation could provide calibration data for later decoding of pure motor imagery. Twelve healthy, right-handed participants completed the experiment. Passive stimulation of the left or right hand generated EEG patterns that were used to train or fine-tune classifiers. The evaluation included common spatial pattern (CSP) features with linear discriminant analysis (LDA), alongside a deep transfer-learning approach.

The study reported performance comparable to conventional MI calibration, with an advantage when fewer calibration trials were available. The methodological contribution is a change in how useful training data are elicited: the user senses an externally controlled stimulus instead of repeatedly producing an abstract imagery task. Similarities between tactile and imagery-related ERD make transfer plausible, while differences between people still require careful evaluation [2].

The experiment did not assess online BCI operation. Its healthy participant group also differs from the patients targeted by many rehabilitation systems. The authors identify evaluation in older users as a future need because tactile sensitivity may change with age. Thus, tactile calibration is a promising optional calibration strategy, not an established replacement for individual assessment in all users [2].

EEG decoding using a dense convolutional Transformer

Ding et al. [3] introduced EEG-Deformer to learn temporal patterns at multiple levels of detail. A convolutional encoder is combined with Hierarchical Coarse-to-Fine Transformer blocks, which include a Fine-grained Temporal Learning branch. A Dense Information Purification module combines processed information from multiple levels. The design addresses the possibility that a conventional CNN-Transformer combination may overlook informative short-duration temporal structure.

The model was evaluated using leave-one-subject-out testing on attention, driving-fatigue,

and mental-workload datasets. Reported accuracy and macro-F1 were 82.72% and 82.36% for attention, 79.32% and 75.83% for fatigue, and 73.18% and 69.99% for workload, respectively [3]. These are separate classification tasks. They should not be interpreted as motor-imagery performance, as clinical recovery rates, or as guaranteed accuracy for a new user.

The study supports richer temporal representations for cross-subject EEG analysis. Its limitations include incomplete coverage of EEG task types and relatively high variability in some datasets. The results also do not establish real-time performance on low-power wearable hardware. Deployment of this architecture would require measurement of memory, processing time, energy use, and any accuracy loss introduced by model compression [3], [4].

A broader decoding perspective is provided by the classification review of Lotte et al. [9] and convolutional-network studies [7], [8]. Traditional pipelines make feature extraction and classification explicit, whereas neural networks can learn representations from EEG. Neither approach removes the need for careful validation.

A model that performs well within a recording session may still encounter difficulty with a new participant or a different session. Comparisons should therefore state the transfer setting, calibration data available, and preprocessing decisions, so that apparent gains can be interpreted in their actual experimental context [9], [11].

Edge AI for portable BCI systems

Nguyen et al. [4] survey the complete Edge AI BCI pipeline, including acquisition hardware, preprocessing, lightweight neural networks, embedded accelerators, and applications. Their systems perspective shows why model accuracy alone is insufficient: electrode quality, analog acquisition, buffering, feature extraction, inference, and feedback all contribute to practical performance.

The survey discusses efficiency techniques such as pruning, quantization, and knowledge distillation. These methods can reduce resource demands, but their usefulness depends on the target processor and the task.

Local processing can reduce dependence on an external connection and limit transmission of raw EEG; it does not automatically provide complete privacy or security. The reviewed implementations also use different datasets and hardware, so their performance figures are not directly interchangeable [4].

Clinical applications and translational limitations

Jain et al. [5] provide a narrative clinical review covering BCI principles, applications, evidence, and practical decision-making. Their discussion places technical achievements in the context of patient abilities, caregiver support, setup burden, access, and clinically meaningful benefit. It also addresses the limitations of evidence across indications, including small samples and heterogeneous protocols.

The clinical review reinforces the need to distinguish demonstration of signal decoding from dependable clinical benefit. Electrode preparation, fatigue, sustained attention, support requirements, and inconsistent performance can affect use outside the laboratory. Larger controlled studies and clearer reporting are needed before broad conclusions can be drawn across conditions [5].

Recent application studies demonstrate the breadth of the field beyond the five core publications. Speech neuroprostheses have decoded attempted speech from implanted neural recordings, including text generation and speech or avatar output [13], [14]. Non-invasive research has also investigated EEG-based control of individual robotic fingers [15].

These examples involve different recording methods and intended outputs. They extend the application context of this review, but their results

should not be used as direct evidence that the proposed EEG rehabilitation architecture can achieve the same performance or clinical benefit.

VI. Comparative Analysis

Table 1 compares the five publications by their evidence type and contribution. The clinical study evaluates motor outcomes, the calibration and decoding studies examine signal interpretation, and the reviews synthesize wider evidence. Their outcomes answer different questions.

Table 1. Comparison of the reviewed BCI publications

Study	Method and setting	Main contribution	Limitations
[1] Zhang et al. 2023	Adaptive MI-BCI with FES; 33 subacute stroke patients.	FM-UE gain: 9.8 ± 5.3 versus 4.3 ± 3.3 points in the control group.	Small clinical sample; intensive training; five lost to follow-up.
[2] Zhong et al. 2024	Tactile ERD transfer; CSP-LDA and deep transfer learning; 12 healthy users.	Passive tactile data supported later MI decoding, including reduced-trial calibration.	Offline evaluation; patient and older-user validation required.
[3] Ding et al. 2025	EEG-Deformer; leave-one-subject-out testing on three cognitive tasks.	Accuracy: attention 82.72%; fatigue 79.32%; workload 73.18%.	Task-specific evidence; variability across users; embedded operation not established.

Study	Method and setting	Main contribution	Limitations
[4] Nguyen et al. 2025	Survey of acquisition, preprocessing, lightweight models and edge hardware.	Connects EEG quality with latency, energy and hardware constraints.	Secondary evidence with heterogeneous tasks and platforms.
[5] Jain et al. 2026	Narrative clinical review of applications and implementation.	Connects technical selection with clinical evidence and practical use.	Heterogeneous evidence; not a single controlled experiment.

What the evidence supports

Together, the studies support a design process that addresses acquisition, calibration, decoding, feedback, and deployment as linked problems. Adaptive assistance and tactile calibration target user-related barriers; richer temporal models target representation quality; Edge AI addresses operational constraints. None of the papers validates all these components together in one portable clinical system [1]–[5].

Why the reported results cannot be pooled

FM-UE improvement measures motor impairment, whereas classification accuracy measures agreement with task labels. Macro-F1 additionally reflects class-specific performance. Different participants, tasks, datasets, and protocols prevent a fair overall ranking. A defensible comparison should preserve these distinctions and assess whether each result answers the intended use-case question.

V. CONCLUSION

This review proposes a seven-stage EEG-based BCI architecture that combines the engineering concerns identified in the literature. It is a research concept rather than an implemented or clinically

validated system. A motor-imagery control task would be the initial use case; attention or fatigue monitoring would require separate task-specific models and validation.

Calibration and model selection

A lightweight CSP-LDA baseline should be established before adding a more complex network. Tactile calibration can then be evaluated as an alternative input procedure, following the rationale of [2].

A compact neural model or compressed Transformer should be retained only if it provides a useful improvement under the selected device's constraints. EEG-Deformer's cognitive-task results alone do not justify assuming superiority for motor imagery [3].

Confidence-aware output

A low-confidence or artifact-contaminated prediction should produce an abstention rather than an automatic command. Any adaptive assistance must be logged separately from the neural prediction so that assisted task success is not mistaken for decoder accuracy.

For an initial engineering prototype, feedback can be a screen-based cursor or virtual hand. Integration with FES would require a separate supervised research protocol and clinical validation, beyond the conceptual design presented here [1], [5].

The proposed signal-quality stage should retain a record of why each window is accepted or rejected. A loss of electrode contact, a large movement artifact, or inconsistent timing can otherwise produce an apparently confident prediction from unsuitable data.

Rejection has its own cost: excessive rejection may leave the user unable to complete a task. Evaluation should therefore report both prediction quality and the proportion of time during which useful control remains available. This would make the trade-off between cautious operation and practical responsiveness visible [4], [5].

Edge implementation and data handling

The edge implementation should measure the entire acquisition-to-feedback delay, rather than inference time alone. Quantization or pruning can be tested after a reference model is established. The evaluation should report model size, peak memory, energy consumption, and performance before and after compression. These measurements would reveal whether a more complex decoder provides a practical benefit on the chosen hardware [4].

Local processing can keep most raw EEG on the device, with access controls and a defined retention period. Stored records should include the model version, calibration condition, rejected windows, confidence values, assisted actions, and timing measurements. Model adaptation should remain traceable, and an earlier validated version should be recoverable. These are proposed engineering controls motivated by the deployment and ethical issues discussed in [4], [5].

Figure 1. Editable workflow for the proposed EEG-based BCI

Stage	Processing and output
1 User and task definition	Select the intended command task, user needs, accessible cues, and feedback mode.
2 EEG acquisition	Acquire time-stamped EEG; record channel configuration and electrode-contact quality.
3 Signal-quality control	Apply task-appropriate filtering and artifact checks; reject unreliable windows.
4 Individual calibration	Compare conventional MI calibration with an optional tactile-assisted transfer pathway.
5 Efficient decoding	Run CSP-LDA or a validated compact neural model; estimate class and confidence.

Stage	Processing and output
6 Decision and feedback	Use confidence and task state to permit a command or request another trial; provide feedback.
7 Monitoring and adaptation	Track errors, delay and drift; review updates before deployment and return to calibration if needed.

Feedback links: Stage 7 informs Stage 4 when recalibration is required; poor signal quality at Stage 3 returns the system to acquisition checks; Stage 6 supplies task feedback to the user for the next trial.

Proposed validation plan

Evaluation should separate offline model development from prospective online use. Data from a test participant must not inform feature normalization, model tuning, or selection. For session-based studies, temporally overlapping windows should remain in the same partition to avoid overly optimistic estimates. Comparisons should use the same task, participants, preprocessing, and evaluation split.

Table 2. Evaluation dimensions for the proposed architecture

Dimension	Measurements	Purpose
Decoding quality	Balanced accuracy, macro-F1, confusion matrix and per-user results.	Check class balance and variability rather than mean accuracy alone.
Calibration burden	Minutes, number of trials, completion rate and user effort.	Compare MI and tactile-assisted calibration at matched budgets.
Online interaction	False commands, abstention rate, task completion and end-to-end delay.	Measure usable control under prospective conditions.

Dimension	Measurements	Purpose
Embedded efficiency	Peak memory, model size, energy and battery duration on stated hardware.	Verify that the full pipeline meets device constraints.
Robustness	Performance across sessions, electrode changes and artifact levels.	Identify drift and conditions that require recalibration.
Clinical translation	Appropriate functional outcomes, adverse events and follow-up in a separate study.	Determine benefit beyond successful EEG classification.

Proposed validation plan

Evaluation should separate offline model development from prospective online use. Data from a test participant must not inform feature normalization, model tuning, or selection. For session-based studies, temporally overlapping windows should remain in the same partition to avoid overly optimistic estimates. Comparisons should use the same task, participants, preprocessing, and evaluation split.

An ablation study should compare the baseline with tactile calibration, adaptation, and compression added individually. This would show which component changes the outcome and whether a gain in one measure is offset by a loss in another. No numerical target or expected improvement is claimed before these experiments are conducted.

VI. Research Gaps and Future Directions

Table 3 translates the limitations of the selected publications into testable research directions. The evidence supports investigation of these questions, but does not establish that a single algorithm can solve all of them.

Table 3. Research gaps and corresponding future work

Research gap	Evidence and implication	Future direction
Calibration transfer	Tactile calibration was assessed offline in healthy users [2].	Evaluate online use, patient populations, age effects and individual sensory differences.
Generalization	EEG-Deformer covers selected cognitive tasks and shows variability [3].	Test new users and sessions; include motor imagery only with dedicated validation.
Clinical evidence	The adaptive study is small; clinical protocols are heterogeneous [1], [5].	Use larger controlled studies with transparent attrition and meaningful follow-up.
Hardware trade-offs	Edge implementations differ in tasks and processors [4].	Benchmark complete pipelines on stated hardware with energy and timing measurements.
Everyday usability	Preparation, attention and support can constrain sustained use [5].	Measure setup time, fatigue, caregiver workload and home-use reliability.
Privacy and oversight	Neural data and adaptive outputs require accountable handling [4], [5].	Define consent, retention, access, update records and user control over operation.

Priorities for practical research

The immediate priority is reproducible comparison under a shared protocol. Studies should document channel selection, sampling, filtering, windowing, class balance, train-test separation, and per-participant performance. Reporting only the best average accuracy can hide users who obtain little

useful control. Confidence intervals and repeated-session testing would make the reliability of a proposed improvement easier to assess.

The next priority is reducing burden without removing user agency. Calibration efficiency, comfortable acquisition, understandable feedback, and the ability to pause should be evaluated alongside decoding. Adaptive systems should also reveal when assistance contributes to task success. This distinction is particularly important when studying the relationship between intention, feedback, and rehabilitation [1], [5].

Longer-term work should examine whether efficient on-device models retain performance under realistic movement and environmental noise. Portability is valuable only if signal quality, response timing, and maintenance remain acceptable. Multimodal sensing may help selected tasks, but additional sensors introduce their own setup, synchronization, and resource costs [4].

A further research priority is maintaining performance over time. EEG distributions can change with attention, fatigue, electrode placement, and recording conditions, so calibration should be treated as an ongoing design issue [11], [12]. A proposed adaptation mechanism should first detect a sustained change, then determine whether a short recalibration or a model update is justified. Updates should be evaluated against an independent set of observations before use. This approach would allow researchers to study whether adaptation improves long-term reliability without confusing temporary fluctuations with genuine changes in user control.

VII. Conclusion

This review examined five publications addressing complementary challenges in brain-computer interfaces. Adaptive MI-based rehabilitation provides clinical evidence that performance-dependent assistance can support participation after stroke. Tactile ERD transfer offers a promising calibration alternative, while EEG-

Deformer demonstrates the value of multiscale temporal representations for selected cognitive classification tasks. The Edge AI and clinical reviews show that portable operation and meaningful use depend on much more than a decoder's average accuracy [1]–[5].

The proposed seven-stage architecture connects these findings through signal-quality control, individualized calibration, efficient decoding, confidence-aware decisions, and monitored adaptation. Its benefit remains a hypothesis until evaluated as an integrated system. Progress should be judged using distinct measures of decoding quality, calibration burden, online reliability, energy use, and, where relevant, clinical outcomes. Larger and more reproducible evaluations are needed to determine which combinations provide dependable benefits across users and settings.

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