A Systematic Review of Trustworthy and Explainable AI Frameworks for Motor Imagery-Based Brain-Computer Interfaces in Robotic Control Systems

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ABSTRACT

This study focuses on the reliability, robustness, and explainability of Motor Imagery-based Brain-Computer Interfaces (MI-BCIs). MI-BCIs can control external devices through imagined movements and have promising applications in neurorehabilitation, assistive robotics, and smart environments. Their practical application is hampered by signal reliability, variable evaluation, and the lack of defined assessment frameworks. A total of 43 peer-reviewed research studies in ScienceDirect, Scopus, and IEEE Xplore were analyzed and divided into six areas: robotic systems, healthcare and neurorehabilitation, smart environments and IoT, trustworthy and secure MI-BCIs, explainable AI, and learning frameworks. This review highlights similar motivations, important hurdles, and field-advancing strategies. The findings show significant repeatability, cross-subject generalization, and reliability gaps. To our knowledge, this is the first comprehensive investigation on the trust, robustness, and explainability of MI-BCI frameworks. Interdisciplinary collaboration, ethical norms, and subject-invariant techniques are needed to expedite MI-BCI development from the lab to the field.

Keywords-motor imagery; brain-computer interface; EEG explainable artificial intelligence; robotic neurorehabilitation; fuzzy MCDM

I. INTRODUCTION

ML and AI have substantially improved MI-BCI accuracy and adaptability. Deep learning can classify over 99% of EEG inputs in controlled experiments [1], allowing real-time robotic limb, mobility assistance, and wearable exoskeleton operation. These technologies can accelerate stroke patients' motor function recovery by 40% and give paralysis sufferers some control in everyday tasks. The clinical practicality of BCI technologies is recognized by the FDA and EU, which can reduce healthcare demands and improve patient autonomy [2]. However, despite advances, MI-BCI devices are restricted to laboratories, with robustness, model transparency, and user trust being key issues. Uneven dynamic performance results from chaotic, non-stationary EEG signals tainted by muscular or ocular aberrations [3, 4]. System scalability is limited by inter-user heterogeneity, requiring more calibration.

AI-driven BCI models are termed "black-box" because they lack transparency, causing clinical trust issues and hindering validation and accountability [5]. The lack of research on brain data ethics and privacy poses data security, system misuse, and user consent problems [6]. Ethics, prejudice mitigation, and real-world application are neglected in favor of classification accuracy [7, 8], but neglect ethical integrity, bias reduction, and real-world applicability [9]. Recently developed hybrid MI-BCI models incorporate visual, tactile, or auditory input, increasing performance and reliability [10]. In addition, evaluation frameworks vary throughout the literature. Filling this gap requires methodological rigor, bias assessment, and data integration [11].

This systematic study synthesizes 43 peer-reviewed publications (2019–2025) from ScienceDirect, Scopus, and IEEE Xplore to overcome these limits. The frameworks are categorized into robotic systems, healthcare, smart environments, security, robust AI, and learning techniques in a unique taxonomy for a trustworthy MI-BCI assessment. Research trends, famous authors, and knowledge gaps were mapped with VOSviewer and Bibliometrix. This review emphasizes future-oriented methodologies for the evaluation of MI-BCI by incorporating subject-invariant learning, eXplainable AI (XAI), and neurosecurity as essential elements to overcome current methodological gaps. Through the integration of data fusion and multi-source signal processing, a structured framework is proposed to strengthen benchmarking practices and improve reproducibility, scalability, and trust in MI-BCI systems. In addition, this study provides ethical and policy-oriented guidelines to support the development of interpretable, human-centered BCI technologies, providing practical directions for researchers, clinicians, and developers to accelerate the translation of MI-BCI from laboratory research to real-world applications.

II. METHODOLOGY

Focusing on MI-BCIs, this systematic study focuses on the advancement of robotic control with dependable and explicable AI. The method adhered to the PRISMA [12] guidelines for literature selection, screening, and synthesis, ensuring the validity and application of the results. Previous literature studies were utilized to inform the systematic review [13]. Figure 1 presents the overall study selection procedure.

A. Database Selection

Three reputable academic databases were selected to retrieve studies, considering their disciplinary relevance and indexing quality.

- ScienceDirect is recognized for its comprehensive collection of peer-reviewed publications in neuroscience, biomedical engineering, and artificial intelligence applications.
- Scopus was selected for its extensive multidisciplinary scope and sophisticated filtering functionalities.
- IEEE Xplore was chosen for its focus on electrical engineering, signal processing, and BCI technology.

These databases were selected based on prior systematic reviews and a scoping exercise confirming their relevance to MI-BCI research.

B. Search Strategy

A comprehensive search was carried out in IEEE, Scopus, and ScienceDirect for English-language publications up to August 2025. A Boolean query combined the terms Motor Imagery, Brain-Computer Interface, and Artificial Intelligence. Keywords were selected to ensure coverage, including emerging trends on trust, explainability, and auditability in MI-BCI.

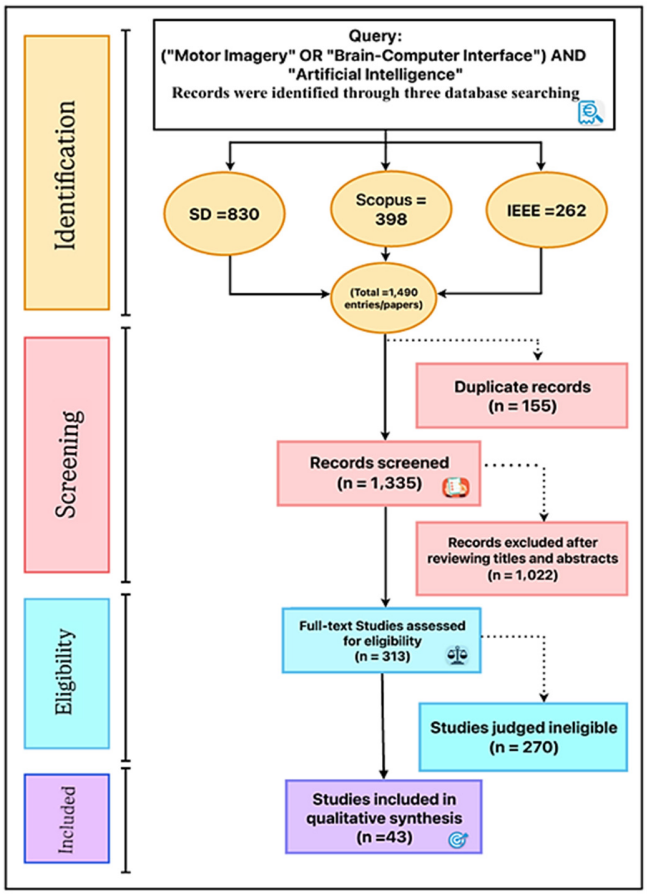

Fig. 1. An outline of the approach used to identify, screen, and include relevant studies in the systematic review of MI-BCI research.

C. Inclusion and Exclusion Criteria

Studies were included if they were published in English, focused on MI-BCI applications, and addressed at least one of the six priority domains: robotics, healthcare/ neurorehabilitation, smart environments/IoT, privacy and security, XAI, or learning frameworks. Only works demonstrating significant technical innovation were considered. Exclusions applied to non-English papers, studies on non-MI paradigms (e.g., P300, SSVEP), purely theoretical works, and applications outside the specified domains. Figure 1 summarizes the overall identification, screening, eligibility, and inclusion process.

D. Study Selection

Similar to previous works [12, 13], this study adhered to the PRISMA guidelines for systematic reviews. A total of 1,490 records were initially identified (Scopus: 398; IEEE: 262; ScienceDirect: 830). After removing 155 duplicates, 1,335 unique papers remained. The title and abstract screening excluded 1,022, while the full-text assessment eliminated 270 more. Ultimately, 43 studies met the inclusion criteria and were retained for qualitative synthesis.

III. COMPREHENSIVE SCIENCE MAPPING ANALYSIS

The rapid expansion of research on MI-BCI has complicated efforts to synthesize knowledge and identify gaps. Although frameworks such as PRISMA help organize findings, they remain limited by subjectivity. To improve objectivity and transparency, this study applied the VOSviewer and Bibliometrix R-tool to map contributions, collaboration patterns, thematic clusters, and research gaps. The following subsections outline the selection criteria and analytical methods used.

A. Annual Scientific Production

From 2015 to 2024, systematic review publications on AI in MI-BCI systems showed steady growth. Fewer than 60 articles were published annually until 2018, with a slight decline in 2019, followed by a continuous increase that peaked at 132 articles in 2024, reflecting growing interest in trustworthy AI for neurorehabilitation, assistive robotics, and explainable decision-making.

B. Word Cloud

EEG, brain-computer interface, and machine learning emerged as the most prevalent terms, with the first having the highest betweenness centrality (79.072) as a conceptual bridge across domains. Other key terms, such as motor imagery, electroencephalography, and AI, emphasize methodological and neurophysiological foundations, while terms like virtual reality highlight growing interest in immersive applications. This reflects the multidisciplinary nature of MI-BCI research, combining neuroscience, computational modeling, and human-centered design.

C. Co-Occurrence

Keyword co-occurrence analysis revealed that MI-BCI research is dominated by computational and neurotechnological concepts, with central terms such as BCI, EEG, and AI. Machine learning and signal processing emerged as key methodological themes, while peripheral keywords (e.g., electrophysiology) indicated narrower roles. This highlights a strong focus on learning-based approaches with emerging opportunities in adaptive and multimodal integration.

D. Country Collaboration Map

The country collaboration map in Figure 2 illustrates co-authorship patterns in MI-BCI research. Asia-Pacific countries, particularly Australia, Singapore, Malaysia, and Hong Kong, show notable connections, with additional links to European partners. Other regions, including Canada, France, Portugal, and Argentina, demonstrate comparatively lower collaboration. Overall, the map reflects regional variations in research activity and cooperation.

IV. FINDINGS AND ANALYSIS: A TAXONOMY

The review highlighted key themes in MI-BCI evaluation frameworks. An objective study using the inclusion criteria divided the 43 papers into six main categories. Subcategories, sections, and subsections were established using trustworthy MI-BCI evaluation frameworks after category analysis. These papers were categorized as follows:

- Robotic Applications: 14 papers
- Healthcare and Neurorehabilitation: 6 papers
- Smart Environments and IoT: 3 papers
- Privacy and Security in MI-BCI: 6 papers
- Robust and Explainable AI for MI-BCI: 7 papers
- Learning Frameworks: 7 papers

A. Robotics Applications

In this category, BCIs use motor imagery for robotic control, such as assistance robots, brain-controlled UAVs, and mobility systems. 14 research studies examined MI-BCI robotics for rehabilitation and movement aid.

1) Robotic Arm and Prosthetics

This subcategory includes 8 of the 14 studies that focus on robotic arms and prosthetics controlled by MI-BCI. These systems enable individuals with motor impairments to operate assistive devices through brain activity, improving mobility and independence. Shared control strategies have been widely applied, such as in [14], which integrated robot vision with non-invasive BCI, significantly improving success rates and reducing task time (p <0.001). Several works employed advanced signal processing and learning algorithms, achieving 99.06% accuracy using 2D-CNN with EEG in [1], while in [2], kinematic models, KNN, and a fuzzy logic controller were combined to precisely translate brain signals into robotic movements. Hybrid approaches have also emerged. For instance, in [15], CSP-JAD with ANFIS enabled four-class MI control on the BCI Competition IV dataset. Deep learning-based systems are prominent, achieving more than 84% accuracy with CNN–LSTM for hexapod control in [16]. In [17], dry and wet electrode systems were compared, showing trade-offs between portability and signal fidelity, while in [11], RBP features were optimized with KNN for upper-limb MI classification. In [18], the effectiveness of LSTM, CNN, and RCNN for real-time robotic arm control without manual feature extraction was demonstrated.

2) Humanoid Robots for Motor Imagery

This subcategory includes three studies that examine the integration of humanoid robots and intelligent control frameworks with MI-BCI systems. These studies aimed to improve the quality of EEG signals and the precision of robotic control through immersive and biologically inspired interaction. In [19], it was shown that using humanoid robots as visual stimuli during MI tasks significantly improves cortico-spinal excitability and clarity of Event-Related Desynchronization (ERD) patterns. In [5], an embedded MI-BCI system was developed to control a hexapod robot using imagined fist movements. EEG signals were acquired through the Emotiv EPOC+ headset and processed on an Altera SoCKit platform using a CNN-LSTM architecture. In [20], TRCA filtering, deep learning networks, and Model Predictive Control (MPC) were combined to develop a brain-controlled mobile robot.

Fig. 2. Country collaboration map in MI-BCI research showing global co-authorship networks and regional variations in research activity.

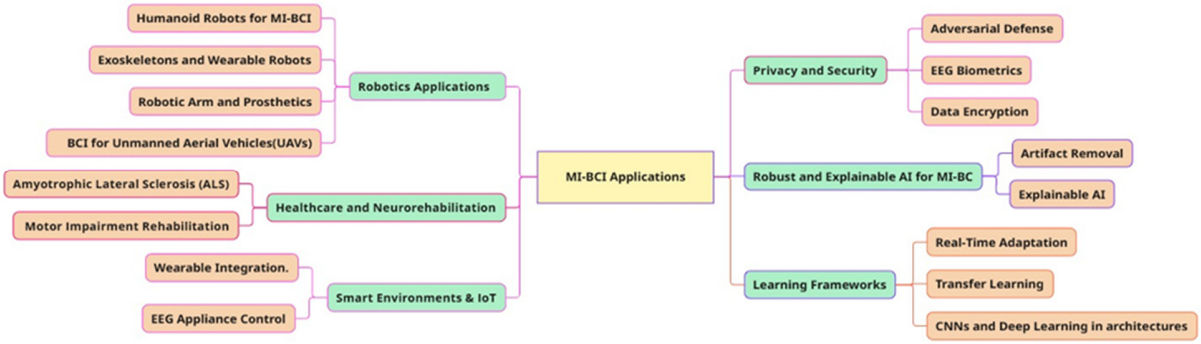

Fig. 3. Taxonomy of MI-BCI Applications

3) BCI for Unmanned Aerial Vehicles(UAVs)

One paper explored the application of MI-BCI for the operation of UAVs in indoor and remote settings. In [21], an MI-BCI system used single-way vision and motor imagery-decision-making to locate 3D indoor targets using a low-speed UAV. The decision subsystem used CSP filtering and a CNN for quaternary classification to assess EEG data from four motor imagery tasks (left/right hand, feet, and tongue). The navigation subsystem used SIFT and BF algorithms to identify obstacles and possible flying.

4) Hybrid BCI for Mobile Robot Control

This subcategory includes 2 of 14 studies exploring hybrid BCI approaches for mobile robot control. In [22], a shared control system combined Augmented Reality (AR), MI-BCI, and eye tracking to control robotic arms using mental imagery. The system used AR to suggest actions based on the user's gaze. This study contributed to improving BCI usability by integrating AR and eye tracking for more practical assistive robotics applications. In [20], a brain-controlled mobile robot system used TRCA filtering, deep neural networks, and MPC, enhancing real-time performance by reducing classification time and ensuring safety by monitoring obstacles. This approach outperformed traditional methods and is suitable for high real-time demand applications.

B. Healthcare and Neurorehabilitation Applications

This subcategory encompasses the integration of MI-BCI into healthcare, including 6 studies.

1) Motor Impairment Rehabilitation

This subcategory includes 3 studies on MI-BCI for motor impairment rehabilitation, focusing on EEG-based neuromodulation and advanced training methods. In [23], the performance variations of MI-BCI systems induced by practice were quantified using EEG changes and Global Field Power (GFP), Dynamic Time Warping (TW), and Mutual Information (MutInf). EEG changes during mental preparation indicate practice levels. This study showed that metrics can be used to monitor user training in BCI systems. In [24], an ES-enhanced MI paradigm was presented for stroke patients' lower-limb rehabilitation. This approach integrated ES with MI tasks to reactivate motor cortical areas and enhance classification performance across models (SVM, KNN, RF, LDA, and EEGNet). ES may increase MI-induced brain activity, facilitating BCI-controlled robotic rehabilitation.

2) Amyotrophic Lateral Sclerosis (ALS)

In [25], a coadaptive BCI model was presented for patients with ALS. Since ALS is progressing, non-stationary EEG signals can hamper MI decoding. The suggested approach addresses this issue. The model dynamically responds to brain activity variability and classifies MI tasks with left-hand, right-hand, and rest states using the Filter Bank Common Spatial Pattern (FBCSP) approach.

C. Smart Environments and IoT

Three studies focused on the role of MI-BCI and the IoT.

1) EEG Appliance Control

The study in [26] focused on utilizing EEG signals for smart appliance control through BMI. An MI-based BCI mouse cursor control system was developed, where a MATLAB system processed EEG inputs from the Emotiv EPOC+ headset. Instead of offline, this semi-online technology allows near-real-time interaction.

2) Wearable Integration

Two studies [27, 28] explored wearable and hybrid BCI solutions within IoT contexts. The first demonstrated a brain-controlled UAV using CPVEP and HMCL controllers, supporting applications in search and rescue, traffic monitoring, and infrastructure inspection. The second integrated MI and SSSEP paradigms via CNN with dry EEG electrodes, achieving robust accuracy across configurations and offering practical adaptability for wearable smart systems.

D. Privacy and Security in MI-BCI

This category discusses EEG biometrics, data encryption, and adversaries in MI-BCI systems, including 6 studies.

1) EEG Biometrics

EEG-based biometrics can provide secure authentication for BCI applications, enabling template revocation and resisting adversarial threats. Poly Cos Graph [29] achieved an EER of 0.68% for motor imagery tasks while preventing raw EEG reconstruction and supporting template renewal. Complementary CNN models [30], with channel selection and 8-bit quantization, reached 82.51% accuracy, setting benchmarks for embedded MI-BCI. GAN-based approaches further enhanced synthetic EEG data generation for scalable, secure, and adaptive systems.

2) Data Encryption

Securing data transmitted through BCIs is a fundamental requirement for ensuring system reliability, especially in sensitive applications such as neurorehabilitation and intelligent interaction. MetaBCI [31] is an open-source platform that integrates key modules for stimulus presentation (Brainstim), signal processing (Brainda), and real-time data flow (Brainflow). This modular design allows safe data processing, real-time feedback, and fast encoding and decoding of brain signals. Meta-BCI makes it easier to build BCIs and provides developers with a flexible environment to include encryption in their processing pipelines. The study in [32] focused on cognitive computing with BCI-based digital twin systems. These studies show that BCI data encryption is moving away from static protection toward frameworks that are user-centered and adaptable.

3) Adversarial Defense

AIDC-CN [33] is a dual-convolutional deep learning model with self- and cross-attention modules for robust MI-EEG classification. Using spectrograms and brain connectivity features, it enhances interpretability and accuracy, outperforming existing methods on four datasets. The MCSCA classifier [34] is a population-based approach influenced by the sine cosine algorithm, segmenting temporal-spectral EEG sub-signals and applying feature weighting for efficiency.

E. Robust and Explainable AI for MI-BCI

This category involves recent breakthroughs in making AI systems more dependable for MI-BCI. Thirteen studies aimed to improve the performance, dependability, and interpretability of MI-BCI systems.

1) Artifact Removal

The initial steps in MI-BCI include artifact reduction. This helps increase the quality of the EEG signal while retaining the brain information relevant to the task. In [35], an adaptive artifact subspace reconstruction technique combined Hebbian and Anti-Hebbian learning methods with the PSP-ASR and PSW-ASR algorithms. This method automatically detects and removes artifacts while maintaining activity-specific brain signals across SSVEP, RSVP, and MI paradigms. In [36], a task-to-task transfer learning technique used Motor Execution (ME), Motor Observation (MO), and Motor Imagery (MI) data to make calibration faster and easier to use, demonstrating the potential of transfer learning in MI-BCI systems. In [37], a multi-layer EEG fusion decoding method with channel selection used MCCM and MLDA. The proposed model was better than others in both accuracy and ease of use.

2) Explainable AI (XAI)

XAI explores intelligent decision-making models to make MI-BCI systems more transparent and make users trust and understand the system operations better. In [38], a model used EEG input, deep learning, and Shapley Additive Explanations (SHAP) to understand MI brain activity. Using motor imagining, it was found that the primary motor cortex (M1), somatosensory cortex (S1), prefrontal cortex (PFC), and posterior parietal cortex (PPC) are activated. Frontal electrodes (F7, F8) and the first 1500 milliseconds of motor imagery were modeled. PRISM [39] uses deep metric learning to classify users by EEG signal similarity to reduce intersubject variability. Integrating specificity and generalizability, PRISM outperformed intersubject models ($p = 0.001$) and intrasubject learning ($p = 0.4$). In [40], a hybrid decoding approach used a dynamic graph convolutional-capsule network (DGC-CapsNet)/EEfNIRS. The study in [41] examined MI-BCI performance with low-abstraction visual support.

F. Learning Frameworks

This category examines learning paradigms that improve MI-BCI. In addition to deep learning and transfer learning approaches, several studies focused on feature-based classification for MI-EEG tasks, highlighting the relevance of traditional signal processing methods [42].

1) CNNs and Deep Learning Architectures

Deep learning, particularly CNNs, has enhanced classification in MI-BCI systems. These models improve spatial, temporal, and frequency domain EEG data extraction, addressing low signal-to-noise ratios, inter-subject variability, and real-time decoding limitations. Early comparisons between deep and regular machine learning were promising. In [43],

BHHSHO hyperparameter optimization was combined with Wavelet Packet Decomposition (WPD), DenseNet, and Convolutional Autoencoders (CAE) in a multi-stage pipeline. DB-ATCNet [44] is a dual-branch temporal attention convolutional network that achieved 87.54% accuracy in subject-dependent evaluations.

2) Transfer Learning (TL)

TL has become crucial for the generalizability of the MI-BCI systems across subjects and sessions. In target domains with little or no labeled data, TL frameworks use knowledge from source domains to improve classification performance due to EEG signal variability. Numerous studies have proposed novel TL-based architectures to address this issue. Neural pattern correlations between contralateral and ipsilateral tasks have been found at important 0.5-1s decision stages, with unique spatial activation patterns. User accessibility and low calibration requirements benefit clinical BCI and neurorehabilitation applications, requiring minimal training and quick installation. By using matrix-based learning and adaptive multi-layer knowledge transfer, a Deep Stacked Transfer Least Square Support Matrix Machine (DST-LSSMM) enhances EEG classification while retaining structural information in feature matrices across three EEG datasets [45].

3) Real-Time Adaptation

Real-time adaptation methods improve the responsiveness of BCI systems to variable brain activity, improving neuro-motor interaction in real-time scenarios. The GD-TIL method [46] enhances MI decoding by employing data augmentation and a Multi-Scale Temporal-Spatial Feature Extractor (MTSFE). A self-supervised task generalization technique enhances generalizability, while a prototype-guided generative replay module ensures stability for old tasks while learning new ones. In [47], an incremental training technique utilized Artificial Neural Networks (ANNs) to classify complicated ADL motor imagery tasks. Action observation was used in the first-person 2D virtual reality experiment. This method significantly outperformed twelve baseline methods, including feature extraction and SVM, KNN, LDA, and NB classifiers.

V. DISCUSSION

Table I summarizes the key application domains, outlining performance, bias risks, and proposed solutions, providing a comparative basis for the discussion.

A. Challenges

Despite major advances, MI-BCI systems face persistent barriers across five domains: signal processing, machine learning, clinical integration, security, and adoption. These challenges are summarized in Table II.

TABLE I. OVERVIEW OF MI-BCI APPLICATION DOMAINS AND RELATED FINDINGS

Ref.	Application	Performance	Risk factors	Improvements
[1]	Assistive and Rehabilitation Robotics	Accuracy: 99.06% (2D-CNN); 97.38% (SNN); 45 ms latency	EEG variability in stroke patients	Adaptive training; multimodal EEG–AR–FES fusion
[16]	Stroke Rehabilitation / VR-Enhanced Exoskeleton	Accuracy: 75.35% (open-loop); 74% (closed-loop gait)	Confounding sensory factors; VR calibration complexity	VR-enhanced MI-BCI with CDF auto-leveling for closed-loop gait rehabilitation
[20]	UAVs and Mobile Robots	Accuracy: 91.14 ± 3.26%; decision time 0.2 s (reduced from 0.51 s)	Real-time delay; safety risks	TRCA + DNN + MPC for safe, real-time navigation
[25]	Neurodegenerative Diseases (ALS Adaptive MI-BCI)	Accuracy: 72.6% (3-class MI over 1-2 months)	EEG non-stationarity; disease progression	Online co-adaptive FBCSP for longitudinal ALS signal stability
[40]	Multimodal EEG-fNIRS MI Decoding	Accuracy: 92.6 ± 4.49%; 92.2 ± 2.95%; 85.3 ± 3.58%	Cross-subject variability; fusion complexity	Dynamic Graph Conv + Capsule Network + Cross-Attention Fusion
[48]	UAV Trajectory Tracking / Visual MI	Accuracy: 91.89 ± 5.55%; successful UAV flight	Low MI quality; path complexity	Visual SP guidance + multi-field CNN with attention
[49]	Neuro-Rehabilitation / Hybrid MI–Somatosensory BCI	Accuracy: 84.09% (overall); 81.82% (poor performers)	Poor MI ability; low signal reliability	Hybrid MI + Somatosensory multi-stimulus feedback to enhance ERD
[50]	UAVs and Mobile Robots / Shared Control BCI	Task completion rate: 94.29% (SLNF); avg time 85.31 s	Safety risks; environmental disturbances	Self-Learning Neuro-Fuzzy (SLNF) + Obstacle Avoidance (OAC) controllers
[51]	Real-Time Adaptation / Fusion-Based MI-BCI	Accuracy: 88.80%; optimized: 90.76%	Channel selection difficulty; redundant EEG features	Enhanced Fusion Framework with sensorimotor band + Choquet/Sugeno integrals
[44]	MI-BCI Classification / Graph-Based Deep Learning	Accuracy: 87.54% (DB-ATCNet); 79.57% & 96.02% (EEG_GENet)	EEG spatial variability; cross-subject generalization	Dual-Branch Attention TCN + EEG_GENet with adaptive multi-order graph embeddings

TABLE II. MAJOR CHALLENGES OF MI-BCI SYSTEMS ACROSS TECHNICAL, CLINICAL, AND INSTITUTIONAL DOMAINS.

Refs.	Challenge	Key issues	Evidence
[31, 35]	Signal and Data Processing	Low SNR, non-stationarity, artifacts, lack of standardized datasets [47]	Adaptive artifact reconstruction; FBCSP; optimized channel selection; dataset imbalance limits generalization
[30, 33, 36]	Machine Learning and Modeling	Inter-/intra-subject variability; poor generalization; inefficiency; opacity	Transfer learning; cluster-based calibration; Capsule Nets for interpretability; quantization for efficiency; latency bottlenecks
[2,24]	Clinical Application	Reduced efficacy in patients vs. healthy users; MI capacity variability; integration with devices is complex	Hybrid MI+SSVEP/FES improved rehabilitation; Fuzzy logic and SNN-based robotic controllers need precise synchronization.
[22, 29, 36]	Security & Reliability	Vulnerability to attacks; cross-session variability	Cancellable EEG biometrics; encryption for UAV; domain adaptation and multimodal AR fusion explored, but limited.
[5, 22]	Adoption & Deployment	Low engagement; long training; unintuitive interfaces; lack of clinical standards	Eye-tracking for reduced task time; feedback-driven self-modulation; lack of validation frameworks and trials.

TABLE III. RECOMMENDATIONS FOR FUTURE MI-BCI RESEARCH ACROSS SIX TRUSTWORTHINESS DIMENSIONS.

Ref.	Recommendation	Key Directions / Evidence
[36, 39]	Subject-Invariant & Calibration-Free	Domain adaptation, transfer/meta-learning; calibration-free models; real-time adaptive loops for robust generalization
[29, 39]	Hybrid & Multimodal Architectures	Integration of MI with SSVEP, fNIRS, EOG, VR/AR, FES; synchronous data fusion; adaptive modality weighting
[22, 30]	Lightweight & Real-Time Wearable Systems	Energy-efficient CNNs (30 μJ/inference); low-channel EEG; latency-aware pipelines; optimized preprocessing
[15, 18, 26, 52]	Standardized Evaluation & Explainability	XAI (Shapley, graph decoding, adaptive explainability); MetaBCI benchmarks; hybrid validation; causally aligned models
[24]	Clinical Usability & Deployment	Patient-centered design; immersive VR/feedback; wearable exoskeletons; long-term clinical trials; regulatory compliance
[29, 30, 35]	Neurosecurity & Data Governance	Cancelable EEG biometrics; adaptive subspace reconstruction; federated learning; quantum-resistant encryption; governance protocols

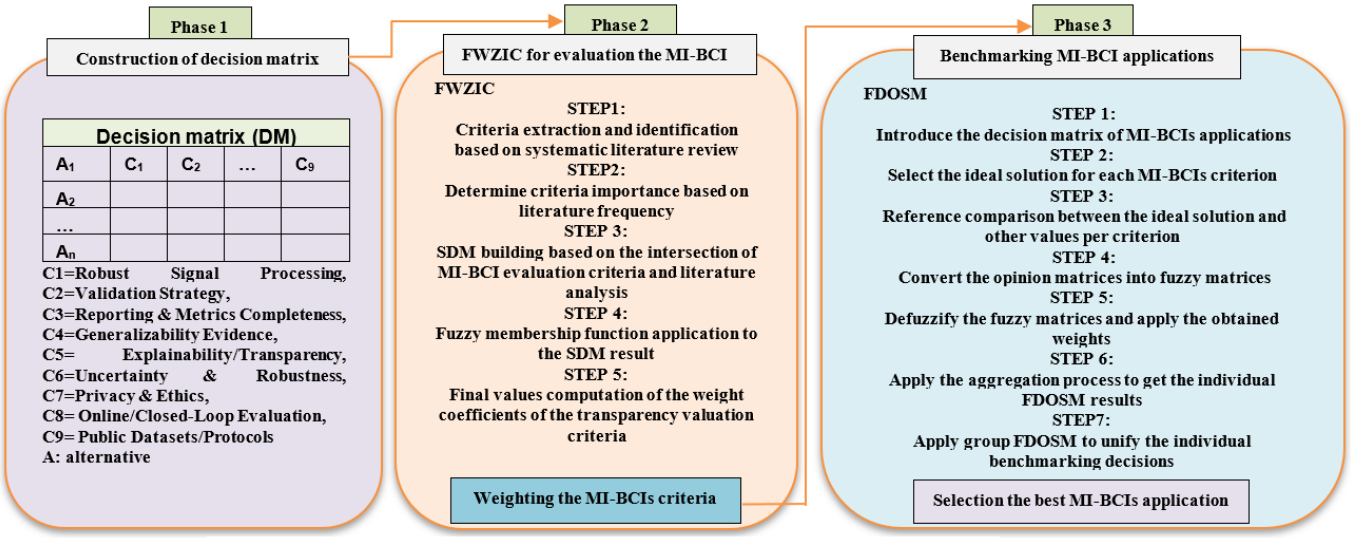

Fig. 4. Proposed method for evaluating and benchmarking of MI-BCI applications.

B. Recommendations

Six key recommendations are proposed for advancing MI-BCI systems: subject-invariant learning, hybrid/multimodal integration, lightweight real-time design, standardized evaluation with explainability, clinical usability, and neurosecurity, as described in Table III.

VI. EVALUATION AND BENCHMARKING OF MI-BASED BCI STUDIES: FUTURE METHODS

Effective fuzzy MCDM algorithms support intelligent and explainable evaluation in biomedical research [48]. This study introduces a three-phase framework to benchmark MI-BCI, as shown in Figure 4, aiming to identify high-quality studies and underrepresented criteria to advance neurorehabilitation and assistive technologies.

A. Phase 1

A decision matrix is constructed using nine methodological criteria (C_1–C_9) extracted from the literature. These criteria cover technical, interpretability, and clinical aspects. Table IV presents the normalized weights and importance levels for each criterion [53].

B. Phase 2

The FWZIC method, an MCDM technique, can be applied to assign relative weights to MI-BCI evaluation criteria. The framework is adapted into a nine-step process based on systematic literature analysis rather than expert judgment [54].

1) Step 1: Criteria Extraction

A total of 43 MI-BCI studies were systematically analyzed to determine the empirical frequency of nine methodological criteria (C_1–C_9), encompassing technical, interpretability, therapeutic, and clinical dimensions.

2) Step 2: Criteria Weighting

The importance of each criterion is derived from its frequency and prominence in the reviewed literature rather than expert judgment [55]. Each criterion is encoded as 1 (present), 0 (absent), or 0.5 (partially fulfilled). Frequencies (f_i) are summed across studies and normalized to obtain the weight distribution.

$$w_j = \frac{f_j}{\sum_{k=1}^{9} f_k} \quad (1)$$

where F_j is the frequency count of criterion C_j and $\sum_{k=1}^{n} f_k = 606.3$ is the total frequency across all criteria.

This quantitative frequency analysis provides the empirical foundation for the fuzzy weighting process, ensuring that each criterion's importance is numerically derived from literature evidence rather than subjective judgment. The normalized weights represent each criterion's empirical prevalence in the literature corpus and its proportionate value. A five-point Likert scale is used to assign linguistic priority levels and numerical scores to each criterion to better understand these frequencies.

3) Step 3: Construction of the Study Decision Matrix (SDM)

The Expert Decision Matrix (EDM) is adapted into a literature-based decision matrix, where each study (S_j) is treated as an alternative and each criterion (C_j) is evaluated by its presence, emphasis, or relevance. The SDM, represented in binary or fuzzy form [55], serves as the basis for subsequent weighting and ranking.

4) Step 4: Fuzzy Fuzzy Membership and Defuzzification

Fuzzy logic is applied to handle variation in the criteria descriptions. TFNs, defined by three parameters (a, b, c), are used for their simplicity and efficiency [56]. These fuzzy values are then defuzzified to obtain crisp weights for each criterion. The membership function of TFNA is:

$$\mu A(x) = \begin{cases} 0 & IF\ x < a \\ \frac{x-a}{b-a} & IF\ \ a \le x \le b \\ \frac{C-x}{C-b} & IF\ \ b \le x \le C \\ 0 & IF\ x > C \end{cases} \quad (2)$$

where $a \le b \le c$.

Let $\tilde{x} = (a_1, b_1, c_1)$ and $\tilde{y} = (a_2, b_2, c_2)$ be two nonnegative TFNs and $\alpha \in R_+$. Following the extension principle, the arithmetic operations are defined as follows [57]:

$$\tilde{x} + \tilde{y} = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \quad (3)$$

$$\tilde{x} - \tilde{y} = (a_1 - c_2, b_1 - b_2, c_1 - a_2) \quad (4)$$

$$\alpha\tilde{x} = (\alpha a_1, \alpha b_1, \alpha c_1) \quad (5)$$

$$\tilde{x} - 1 \cong \left(\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}\right) \quad (6)$$

$$\tilde{x} \times \tilde{y} \cong (a_1 a_2, b_1\, b_2, c_1\, c_2) \quad (7)$$

$$\frac{\tilde{x}}{\tilde{y}} \cong \left(\frac{a_1}{c_2}, \frac{b_1}{b_2}, \frac{c_1}{a_2}\right) \quad (8)$$

Table IV shows the TFN of each linguistic word. This table shows all language characteristics used to evaluate MI-BCI criteria as TFNs produced from literature-based scoring. A normalized weight and Likert term (e.g., Very important, Moderately important, Not important) is given to each criterion C_j based on its frequency and contextual emphasis in the studied literature. Fuzzy aggregation was achieved by mapping linguistic concepts to numerical scores and encoding them as TFNs.

1. The ratio of fuzzification data is determined using (9). The preceding equations are employed with TFNs [58].

$$\frac{ImP(\widetilde{E1}/C_1)}{\sum_{j=1}^{n} ImP(\widetilde{E_1}/C_1 j)} \quad (9)$$

where $ImP(\widetilde{E_1}\ /\ C_1)$ represents the fuzzy number of $ImP(E_1\ /\ C_1)$.

2. To determine the final fuzzy values of the weight coefficients of the criterion $(\widetilde{w_1}, \widetilde{w_2}, \ldots, \widetilde{w_n})^{\bar{T}}$, the mean values should be determined. The fuzzy literature-based Study Decision Matrix ($\widetilde{SDM}$) is utilized to calculate the final weight value of each MI-based BCI criterion using (10).

$$\widetilde{\omega_j} = \frac{\sum_{i=1}^{m} \left(Im\,p(\widetilde{E_{ij}}/C_{ij}) / \sum_{j=1}^{n} 1mp(\widetilde{E_{ij}}/C_{ij})\right)}{m} \quad (10)$$

for $i = 1,2,3, \ldots m$ and $j = 1,2,3, \ldots n$.

3. The centroid approach is the most prevalent defuzzification technique to find the final weight. Using TFNs, the mathematical expression for this procedure is $(a + b + c)/3$. Before computing the final values of the weight coefficients, the weight of importance should be allocated to each criterion based on the total weights of all MI-based BCI criteria for the rescaling purpose used in this step.

5) Step 5. Final Weight Computation

Using the fuzzy data from Step 4, the final weight coefficients $(w^1 \ldots w^9)^T$ are calculated for the nine evaluation criteria (C_1–C_9). These normalized weights provide the basis for applying the FDOSM method in the next phase [58]. The resulting normalized weights quantitatively represent the proportional methodological emphasis observed in the reviewed corpus. These values serve as an interpretable and reproducible measure of the MI-BCI evaluation landscape.

TABLE IV. CONSOLIDATED WEIGHTS, IMPORTANCE LEVELS, LINGUISTIC TERMS, AND TFNS FOR MI-BCI EVALUATION CRITERIA

C	W	P	LT	TFN	S
C_1	0.145	14.5%	Moderately important	(0.30,0.50, 0.75)	3
C_2	0.121	12.1%	Moderately important	(0.30,0.50, 0.75)	3
C_3	0.153	15.3%	Very important	(0.50,0.75, 0.90)	4
C_4	0.026	2.6%	Not important	(0.00,0.10, 0.30)	1
C_5	0.140	14.0%	Moderately important	(0.30,0.50, 0.75)	3
C_6	0.139	13.9%	Moderately important	(0.30,0.50, 0.75)	
C_7	0.018	1.8%	Not important	(0.00,0.10, 0.30)	
C_8	0.016	1.6%	Not important	(0.00,0.10, 0.30)	
C_9	0.142	14.2%	Moderately important	(0.30,0.50, 0.75)	

C: Criterion, W: Weight, P: Percentage, LT: Likert Term, S: Score

C. Phase 3

FDOSM is a fuzzy MCDM method to rank MI-BCI applications. It supports both individual and group decision-making and consists of three main units: data input, data transformation, and data processing [59].

VII. SCIENTIFIC SIGNIFICANCE OF THE PROPOSED FWZIC+FDOSM FRAMEWORK

The proposed fuzzy MCDM framework introduces a quantitative, transparent, and reproducible approach for evaluating MI-BCI research. By combining FWZIC and FDOSM, it transforms qualitative judgments into data-driven numerical evidence. In the FWZIC phase, the relative importance of nine criteria is derived from the frequency of their occurrence across the 43 studies, using a Gaussian membership function to convert linguistic ratings into continuous fuzzy weights, ensuring objectivity and consistency. The FDOSM phase then benchmarks studies through multidimensional aggregation of robustness, explainability, generalizability, and ethical integrity, producing interpretable quantitative scores for ranking. Together, these phases form the first unified and standardized evaluation model for MI-BCI methodological rigor, advancing the field through transparent weighting, harmonized performance reporting, and reproducible benchmarking of trustworthy and XAI systems.

1) Data Input Unit

The method evaluates m alternatives (e.g., MI-BCI applications) against n criteria (C_1-C_n) from the literature, forming a Decision Matrix (DM) that is transformed into an opinion matrix using linguistic or fuzzy assessments.

2) Data Transformation Unit

Each criterion is optimized using one of the following strategies:

- Minimum value for cost-type criteria
- Maximum value for benefit-type criteria
- Critical value for context-dependent criteria [60]

This ensures appropriate evaluation logic before fuzzy aggregation and ranking.

3) Step 1: Select the Optimal Solution (MI-BCI application).

The optimal solution can be described as:

$$A^* = \left\{[\left(\underset{\mathrm{i}}{max}\ Vij \backslash Jay \in J\right), \left(\underset{\mathrm{i}}{min}\ VijJay \in J\right) \quad (11)\right.$$

where $(O^{pij} \in I.J)\mathrm{i} = 1.2.3 \ldots . M]\}$

4) Step 2: Compare Responses

This step compares the optimum answer to alternative values (remaining SMI-BCI applications) based on the criterion, with weights depending on the assessment criteria. The significance of differences between the perfect solution and alternatives may be subjectively assessed, as shown in:

$$OPlang = \left\{\left(\left(\tilde{v}_{ij} \otimes v_{ij} \middle| j \in J\right).\middle| i = 1.2.3 \ldots . . m\right)\right\}$$

The opinion matrix is a fuzzy comparison of MI-BCI applications to the ideal solution across all criteria. TFNs in FDOSM's last block construct a fuzzy opinion judgment matrix. Table IV describes linguistic phrases to their TFNs. The arithmetic mean can aggregate fuzzy data across criteria for each choice. Ranking and defuzzification are possible with each application's fuzzy scores.

The Bibliometric Decision Matrix (BDM) is converted into a fuzzy opinion matrix by replacing linguistic terms with TFNs defined by their membership functions.

$\tilde{x} = (a_1, b_1, c_1)$ and $\tilde{y} = (a_2, b_2, c_2)$ be two nonnegative TFNs and $\alpha \in R_+$. Following the extension principle, the arithmetic operations are defined as follows:

$$A_{m(x)} = (\sum(a_f + a_m + a_1)\ (b_f + b_m + b_1)$$
$$(c_f + c_m + c_1))/n \quad (12)$$

Defuzzification is performed using the centroid method, where the lowest mean score indicates the best ranking. In external aggregation, evaluation matrices from different MI-BCI studies are processed individually based on the defined criteria. The results of each study's decision matrix are then aggregated into the final benchmarking outcome using an arithmetic mean. In this case, the study evaluations are aggregated after the individual rankings have been determined.

VIII. WEIGHT DERIVATION SUMMARY AND VALIDATION

The weighting process is designed to ensure objectivity and reproducibility in evaluating MI-BCI methodological rigor. A total of nine evaluation criteria were extracted from 43 peer-reviewed studies by systematic literature coding. The relevance of each criterion is assessed according to its frequency of occurrence in the reviewed corpus—classified into three linguistic categories: Good (1.0), Moderate (0.5), and Poor (0.0), representing strong, partial, or absent methodological presence, respectively. The frequency-based evaluation matrix is then aggregated, and the total frequency ($\Sigma f_k = 606.3$) is normalized using the FWZIC model to derive proportional weights for each criterion. To minimize subjectivity, no expert input is employed; instead, all scores are computed empirically from the literature. The linguistic ratings are then converted into quantitative values using a Gaussian (bell-shaped) membership function that smooths the transition between qualitative categories and enables the application of TFNs. This conversion provides continuous numerical representations of importance, capturing subtle variations in emphasis among studies. Defuzzification is performed using the centroid method to obtain the final crisp weights for each of the nine MI-BCI evaluation criteria. These normalized weights can be later validated through comparative analysis within the FDOSM benchmarking phase, confirming proportional influence and methodological consistency across all criteria. This frequency-driven and fuzzy-logic-enhanced weighting process provides explicit numerical transparency and empirical justification for each assigned weight. This advances MI-BCI evaluation by transforming qualitative methodological patterns into quantifiable, reproducible benchmarking criteria through the integrated FWZIC+FDOSM framework.

IX. CONCLUSION

This systematic review synthesized 43 peer-reviewed studies on trustworthy and explainable frameworks for MI-BCIs applying the PRISMA method, bibliometric mapping, and a structured taxonomy. The analysis revealed persistent gaps in cross-subject generalization, interpretability, ethical

integrity, and benchmarking practices. Although recent advances in deep learning, hybrid multimodal systems, and neurosecurity techniques have improved performance, most studies remain limited to controlled laboratory settings. To strengthen the rigor of the evaluation, this review introduced an MCDM framework that combines FWZIC and FDOSM. By weighting nine methodological criteria, including robustness, explainability, generalizability, and privacy, this approach demonstrates a practical pathway for benchmarking MI-BCI research with greater consistency and reduced bias. The integration of fuzzy linguistic terms and TFNs further enabled the translation of qualitative judgments into quantifiable outcomes, laying the groundwork for a more systematic quality assessment in the field.

Policy frameworks should embed neuroethical safeguards and trustworthiness requirements before clinical deployment, while automated bibliometric and fuzzy MCDM tools can support more transparent and reproducible evaluation. Ultimately, advancing trustworthy MI-BCI systems requires an interdisciplinary, hybrid approach in which technical innovation, ethical compliance, and interpretability converge. By integrating robust AI, neurosecurity, and explainability within standardized evaluation frameworks, MI-BCIs can evolve from experimental prototypes to safe, transparent, and socially responsible technologies for rehabilitation, assistive robotics, and human-machine interaction.

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