Advancements in BCI-Based Neurofeedback Systems for Working Memory: A Systematic Review

Review Paper

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Abstract *– Brain-Computer Interface (BCI)-based neurofeedback has emerged as a potentially effective, non-invasive method for enhancing working memory and facilitating cognitive training. Conversely, the methodological heterogeneity characterizing the current research presents a challenge in establishing consistent conclusions concerning system design and efficacy. This systematic review seeks to synthesize the existing body of evidence concerning the design, evaluation, and reported efficacy of BCI-based neurofeedback systems, with a particular focus on their application in enhancing working memory. Adhering to PRISMA guidelines, a structured literature search was performed across Scopus, Web of Science, PubMed, and IEEE Xplore, culminating in the inclusion of 21 studies in qualitative synthesis. The results indicate the clear dominance of EEG-based architectures, with frequency-domain neural features, particularly those derived from alpha-, theta-, and ratio-based measures, being the most prevalent signals utilized. Visual feedback interfaces were the most commonly used, even though some studies used gamified, mobile, or immersive environments. Regarding the evaluation of the results, sham and passive control groups were often used. However, the methods were highly heterogeneous, and long-term follow-up assessments were relatively rare. The reported effectiveness findings were positive but varied. Some studies showed improvements in working memory, while others reported mixed, task-specific, or null effects. A consistent pattern observed was that the successful alteration of the specific neural characteristic did not invariably correlate with demonstrable cognitive enhancement. Based on these findings, this review proposes design and validation guidelines aimed at improving methodological consistency, strengthening evaluation practices, and enhancing comparability across future BCI-based neurofeedback studies.*

Keywords: *Brain-Computer Interface (BCI), neurofeedback, working memory, systematic review, EEG, cognitive training.*

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1. INTRODUCTION

Recent neurotechnology breakthroughs have increased the pace of brain-computer interface (BCI) development, especially closed-loop interfaces that can modulate brain processes in real time. By translating neural activity into computational commands, BCIs have expanded opportunities for human-computer interaction across healthcare, assistive technology, and cognitive training [1, 2]. Within these applications, working memory has become an especially important target because of its central role in executive functioning, reasoning, learning, and goal-directed behavior [3].

Working memory relies on the coordination of frontoparietal brain systems and is tightly linked to oscillatory activity in particular frequency bands, particularly theta (4-8 Hz) and alpha (8-12 Hz) rhythms [4, 5]. These neural signatures provide a physiological basis for neurofeedback interventions aimed at enhancing cognitive performance. In non-invasive BCI, electroencephalography (EEG) or functional near-infrared spectroscopy (fNIRS) is typically used to record brain activity. Neural responses, such as spectral power changes, are then extracted and converted into visual or auditory feedback [6, 7]. Generally, neurofeedback systems based on BCI are designed to adhere to a typical signal-processing pipeline, which

includes signal acquisition, preprocessing (e.g., filtering and artifact removal), feature extraction, and the conversion of neural features into real-time feedback signals [8]. Through this closed-loop process, users can observe and gradually regulate the neural activity associated with their cognitive states.

Despite promising findings, BCI-based neurofeedback systems for working memory remain highly heterogeneous in both design and evaluation. Studies differ considerably in signal acquisition methods, preprocessing procedures, feature extraction techniques, feedback modalities, adaptive thresholding, and outcome measures [3, 9, 10]. Such methodological variability complicates the comparison of results across studies, the determination of common design principles, and the transition to standardized system development. Consequently, there is mixed reporting on the benefits of working memory enhancement, which in many cases is highly influenced by the experimental protocol used [7, 11, 12].

The existing literature on BCI-based neurofeedback and working memory can be grouped into several thematic strands. Design-oriented reviews have explored the problems of usability, engagement, personalization, and adaptive feedback in working-memory interventions, especially from a design-element viewpoint [13]. Conceptual and human-computer interaction-oriented reviews have examined working memory in EEG-based systems, emphasizing theoretical foundations and interface design rather than neurofeedback system integration [14]. Systematic reviews and meta-analyses have been outcome-oriented to examine the effectiveness of neurofeedback in enhancing memory, frequently in a particular population or frequency band, e.g., older adults or theta-based protocols [15, 16]. Implementation challenges and practical applicability have also been reviewed in population- and application-oriented reviews in groups like healthy older adults and individuals with mild cognitive impairment [17]. Despite the useful information presented in these studies, they primarily focus on specific aspects of the area but not on the overall design and assessment of BCI-based neurofeedback systems in relation to working memory.

Combined, the current literature remains incomplete in terms of a systematic synthesis of the design and evaluation of BCI-based neurofeedback systems for working memory in the entire closed-loop workflow. The key technical and evaluative aspects of these systems, such as signal acquisition, preprocessing, feature extraction, feedback architecture, adaptive control, and validation strategies, have not been adequately incorporated in prior reviews. Consequently, it is still hard to tell how these design decisions are integrated in practice and how they affect the reported neural and behavioral results.

To fill this gap, the current systematic review takes a system-level approach based on the closed-loop architecture of BCI-based neurofeedback systems. It integrates empirical research to determine common trends in signal acquisition, feature extraction, feedback design, control strategy, and outcome evaluation, and evaluates the evidence of working memory improvement. This review offers a more integrated foundation to the current design practice and seeks to inform future methodological refinement and standardization by uniting these dimensions.

The research questions (RQs) in this study are as follows:

- RQ1: How are BCI-based neurofeedback systems for working memory designed in terms of signal acquisition, feature extraction, feedback mechanisms, and adaptive control strategies?
- RQ2: How are these systems evaluated, including the experimental design, control conditions, performance metrics, and methodological rigor?
- RQ3: What evidence supports the effectiveness of BCI-based neurofeedback in improving working memory?

2. METHODOLOGY

This systematic review was conducted to ensure transparency and reproducibility in the evaluation of BCI-neurofeedback systems for working memory in accordance with PRISMA 2020 [18]. The review was not prospectively registered in a public database such as PROSPERO. However, it followed a predefined methodology based on PRISMA 2020 guidelines. The inclusion criteria and search strategies were established before data extraction.

2.1. SEARCH STRATEGY AND INCLUSION CRITERIA

A predefined search strategy and inclusion criteria were used before starting the screening process. The review included articles published between 1 January 2014 and 28 February 2026. This timeframe was chosen to capture the time when BCI systems, especially portable and non-invasive EEG-based systems, became more practically feasible and were more frequently used in real-time, closed-loop neurofeedback applications. It is also associated with the transition of previous offline signal processing research to more practical and user-friendly applications, particularly in the cognitive training and working memory literature.

The literature search was conducted using four major databases: Scopus, Web of Science (WoS), PubMed, and IEEE Xplore. These databases were chosen for their wide interdisciplinary coverage, spanning biomedical engineering, signal processing, human-computer interaction, and cognitive neuroscience. The search strategy was a combination of controlled vocabularies and free-text terms with standard Boolean operators (AND, OR). Synonyms and related keywords were added to enhance the accuracy of retrieval, including terms associated with brain-computer interface and neuro-

feedback, working memory and task-specific terms, and EEG and fNIRS. Besides general working memory terms, task-specific keywords like n-back, Sternberg, Corsi, and complex span were also added to identify the relevant experimental studies.

The search strategy was developed based on three conceptual blocks: (1) brain-computer interface and neurofeedback; (2) working memory descriptors; and (3) EEG or fNIRS modalities. These blocks were linked by the AND operator, whereby the studies retrieved had to meet all three elements. Where needed, syntax modifications and field limitations such as title-abstract searching were used based on the needs of each database, but the same underlying Boolean logic was used. Table 1 shows the complete database-specific search queries used in this review.

Table 1. Database-specific search queries

Database	Search Query
Scopus	TITLE-ABS-KEY (("brain-computer interface" OR "brain computer interface" OR BCI OR neurofeedback OR "EEG neurofeedback" OR "neurofeedback training" OR "closed-loop" OR "closed loop") AND ("working memory" OR "working memory training" OR "memory training" OR "cognitive training" OR "cognitive enhancement" OR n-back OR nback OR Sternberg OR Corsi OR "complex span") AND (EEG OR electroencephalography OR fNIRS OR "functional near-infrared spectroscopy"))
Web of Science	TS = (("brain-computer interface" OR "brain computer interface" OR BCI OR neurofeedback OR "EEG neurofeedback" OR "neurofeedback training" OR "closed-loop" OR "closed loop") AND ("working memory" OR "working memory training" OR "memory training" OR "cognitive training" OR "cognitive enhancement" OR n-back OR nback OR Sternberg OR Corsi OR "complex span") AND (EEG OR electroencephalography OR fNIRS OR "functional near-infrared spectroscopy"))
PubMed	("brain-computer interface" OR "brain computer interface" OR BCI OR neurofeedback OR "EEG neurofeedback" OR "neurofeedback training" OR "closed-loop" OR "closed loop") AND ("working memory" OR "working memory training" OR "memory training" OR "cognitive training" OR "cognitive enhancement" OR n-back OR nback OR Sternberg OR Corsi OR "complex span") AND (EEG OR electroencephalography OR fNIRS OR "functional near-infrared spectroscopy")
IEEE Xplore	("brain-computer interface" OR "brain computer interface" OR BCI OR neurofeedback OR "EEG neurofeedback" OR "neurofeedback training" OR "closed-loop" OR "closed loop") AND ("working memory" OR "working memory training" OR "memory training" OR "cognitive training" OR "cognitive enhancement" OR n-back OR nback OR Sternberg OR Corsi OR "complex span") AND (EEG OR electroencephalography OR fNIRS OR "functional near-infrared spectroscopy")

The eligibility criteria were defined using a modified PICO framework and have been summarized in Table 2.

Table 2. PICO-based eligibility criteria

PICO Component	Description
Population (P)	Human participants that went through training sessions in working memory regardless of their age and cognitive status.
Intervention (I)	BCI-based neurofeedback programs (EEG or fNIRS) that should be implemented to improve cognitive ability.
Comparison (C)	Experimental studies with control or comparison groups, e.g., randomized controlled trial, or quasi-experimental studies, and user-testing protocols.
Outcome (O)	Empirical data about the improvements of working memory performance, changes to the neurophysiological parameters, and system usability.

Studies were included if they employed a closed-loop BCI-based neurofeedback system aimed at improving working memory and provided empirical validation using human participants. Peer-reviewed journal articles and conference proceedings for English language studies only were considered eligible. Meanwhile, the exclusion criteria were limited to studies that were only focused on theoretical models, those that only performed offline signal processing without coming up with neurofeedback intervention, animal experiments, or studies that applied non-BCI cognitive interventions. Studies were also excluded if they lacked sufficient methodological detail to allow for a comprehensive technical evaluation.

2.2. STUDY SELECTION AND DATA EXTRACTION

The study selection process followed the PRISMA guidelines and consisted of four stages: identification, screening, eligibility assessment, and inclusion. The first database search returned 1,448 records. After removing 612 duplicate records, 836 records remained for title and abstract screening. Of these, 780 records were excluded as they were not relevant to BCI-based neurofeedback systems or working memory. During the full-text assessment phase, 56 articles were assessed for their eligibility with 35 failing to satisfy the predetermined inclusion criteria and eliminated accordingly. As a result, 21 studies were included in the qualitative synthesis. The overall selection process is illustrated in Fig. 1.

Two reviewers independently selected the studies and extracted the data. The variables extracted were system-level features, including signal-acquisition modality, electrode configuration or sensor arrangement, preprocessing and feature-extraction algorithm, feedback structure, training protocol, control strategy, and any neural and behavioral results reported. Any disagreements between reviewers were resolved through discussion until consensus was reached. The reviewers showed consistent agreement on the extracted variables due to the well-defined eligibility criteria and the relatively objective nature of the variables. Therefore, a formal inter-rater reliability statistic (e.g., Cohen's kappa) was not calculated.

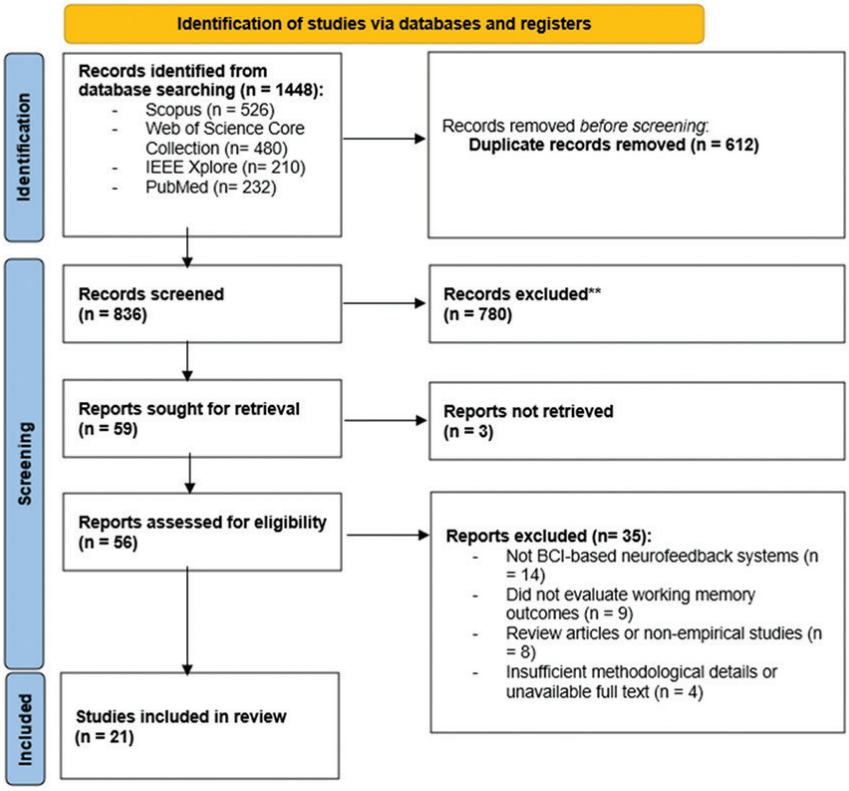


Fig. 1. PRISMA flow diagram illustrating the literature search, screening, and study selection process

2.3. QUALITY ASSESSMENT AND RISK OF BIAS

The methodological quality of the included studies was evaluated using the Joanna Briggs Institute (JBI) critical appraisal tools for randomized and quasi-experimental studies [19, 20]. Two reviewers independently assessed the experimental design, allocation procedures, control conditions, outcome reporting, and potential sources of bias.

Overall, the included studies were generally of moderate methodological quality. Common limitations included relatively small sample sizes, limited blinding due to the operational characteristics of BCI hardware, and short follow-up durations for assessing long-term effects. A summary of the methodological appraisal and principal limitations of the included studies is presented in Table 3. These methodological constraints were taken into account during the qualitative synthesis of system effectiveness.

Across the included studies, several recurring sources of bias were identified. Selection bias was mainly related to the small and non-representative sample populations. Performance and detection bias were also relevant due to limited blinding and the interactive nature of neurofeedback interventions. In addition, variability in the control conditions, including the absence of sham or active controls in some studies, introduced challenges in isolating intervention-specific effects. Short intervention durations and limited follow-ups further contributed to the uncertainty in assessing long-term outcomes. These sources of bias were considered when interpreting the findings of the review.

Table 3. Summary of the methodological appraisal and principal limitations of the included studies

Study	Design	Methodological Appraisal	Principal Limitation
[21]	RCT	Higher rigor	Short training duration
[22]	Quasi-exp.	Moderate rigor	No randomization
[23]	Quasi-exp.	Moderate rigor	Historical control
[24]	RCT	Moderate rigor	Reduced training dosage
[25]	RCT	Higher rigor	Short-term validation only
[26]	RCT	Moderate rigor	Unblinded waitlist control
[27]	RCT	Moderate rigor	Small sample size (*n*=17)
[28]	RCT	Moderate rigor	Restricted demographic
[29]	RCT	Moderate rigor	Passive control group
[30]	RCT	Higher rigor	Baseline memory differences
[31]	Quasi-exp.	Moderate rigor	Quasi-random assignment
[32]	RCT	Moderate rigor	High attrition rate
[33]	RCT	Moderate rigor	Open-label design
[34]	RCT	Moderate rigor	Small sample size (n=30)
[35]	RCT	Moderate rigor	Very small sample size (n=16)
[36]	RCT	Higher rigor	Relatively small sample size (n=40)
[37]	Quasi-exp.	Moderate rigor	Historical control
[38]	RCT	Moderate rigor	Restricted demographic (LD students only)
[39]	RCT	Moderate rigor	Passive control group
[40]	Quasi-exp.	Moderate rigor	Lacked a control group
[41]	RCT	Higher rigor	Single-session protocol

Note: RCT = Randomized Controlled Trial, Quasi-exp. = Quasi-experimental study.

2.4. LIMITATIONS OF THE SEARCH AND METHODOLOGY

Despite drawing from a considerably wide pool of databases, this study is not without limitations. The review was restricted to English language publications, which may have resulted in the exclusion of relevant studies published in other languages. Additionally, although major interdisciplinary databases were included, some relevant studies indexed exclusively in other repositories may not have been captured.

Furthermore, there was substantial methodological heterogeneity across the included studies. Variations in participant populations, signal modalities (EEG and fNIRS), feature extraction approaches, neurofeedback protocols, control conditions, and working memory outcome measures limited the comparability of the results. Due to this variability, conducting a quantitative meta-analysis was not considered appropriate, as it could lead to unreliable or non-interpretable effect size estimates. Therefore, this review adopted a structured qualitative synthesis to provide a more meaningful interpretation of the findings.

3. RESULTS

A total of 21 studies met the inclusion criteria and were included in the qualitative synthesis. The main characteristics of the included studies are summarized in Table 4. Rather than reviewing each study sequentially, the following subsections synthesize the findings based on recurring patterns in signal acquisition, signal processing, feedback architecture, experimental design, and behavioral outcomes. The populations of the studies included were diverse and comprised of students, healthy adults, older adults, athletes, and clinical populations, including stroke patients, individuals with mild cognitive impairment (MCI), and students with learning disabilities. The sample sizes were between 15 and 227. Because of the heterogeneity of the methods and outcomes among the studies, the results are described as a qualitative synthesis but not a statistical aggregation.

Table 4. Summary characteristics of the included studies

Study	Sample Size (Population)	Signal Modality / Neural Target	Training Protocol / Comparator	Main Findings
[21]	48 (Healthy)	EEG: theta/alpha ratio	3 days; sham, behavioral, and no-training controls	Increased theta/alpha ratio and improved WM accuracy compared with controls
[22]	64 (Stroke/ Healthy)	EEG: SMR or upper alpha	Up to 10 sessions; treatment-as-usual comparator	SMR improved visuospatial memory, while upper alpha improved WM
[23]	63 (Older Adults)	EEG: motor imagery bands (12, 18, 21 Hz)	5 weeks; passive control	Increased trained-band power and broader memory-related improvement
[24]	30 (Older Adults)	EEG: individualized alpha and theta	8 days; sham, cognitive training, and combined training arms	Increased alpha/theta activity and improved matrix rotation performance
[25]	30 (Healthy)	EEG: alpha (8-12 Hz)	12 sessions; active sham control	Increased alpha activity and improved WM and episodic memory
[26]	227 (Older Adults)	EEG: personalized score	24 sessions plus booster sessions; waitlist control	No significant overall WM improvement; subgroup improvement in delayed memory and language
[27]	17 (Older Adults)	EEG: SMR (12–15 Hz)	10 sessions; sham and no-neurofeedback controls	Improved visual WM accuracy and increased neural efficiency
[28]	20 (Healthy)	fNIRS	3 sessions; passive control	Increased functional connectivity and improved 3-back accuracy and reaction time
[29]	27 (Students)	EEG: theta/low-beta ratio	3 days; passive control	Improved episodic and semantic memory, but not WM
[30]	27 (MCI)	EEG: upper alpha (PAF-based)	10 sessions; sham control	Improved composite memory score, maintained at 30-day follow-up
[31]	21 (Healthy)	EEG: upper alpha	5 days; active VR-based comparison	Improved 3-back distractor accuracy associated with neurofeedback learning
[32]	86 (Older Adults)	fNIRS	4 weeks; active control	Improved general cognition and memory-related outcomes, but not specific WM
[33]	36 (Students)	EEG: alpha	20 sessions; passive control	Both groups improved behaviorally; only the neurofeedback group showed stronger theta-band connectivity
[34]	30 (Healthy)	EEG: alpha	5 days; passive control	WM updating improved only in successful learners
[35]	16 (Healthy)	EEG: alpha	8 sessions; passive control	Increased alpha power and reduced n-back error rates
[36]	40 (Healthy)	EEG: alpha	5 days; sham control	Improved visual WM capacity and precision, but not all task outcomes
[37]	101 (Healthy)	EEG: theta or high alpha	Single session; active control	Increased target frequencies, but WM improvement was non-specific
[38]	34 (LD Students)	EEG: alpha/theta	20 sessions; passive control	Improved WM and attention, maintained at 2-month follow-up
[39]	40 (Students)	EEG: alpha	8 days; passive control	Increased alpha amplitude, but no WM improvement beyond practice effects
[40]	15 (Stroke/ MCI/HC)	EEG: sample entropy	3 days; no control	Improved task scores and distinct EEG patterns across participant groups
[41]	48 (Athletes)	EEG: alpha (PAF-based)	Single session; sham control	Improved n-back accuracy and visuospatial memory recall

Note: WM = Working Memory, HC = Healthy Controls, LD = Learning Disabilities, MCI = Mild Cognitive Impairment, SMR = Sensorimotor Rhythm, PAF = Peak Alpha Frequency, VR = Virtual Reality.

A generalized closed-loop BCI architecture synthesized from the reviewed studies is illustrated in Fig. 2. As the figure shows, these systems typically involve a sequence of signal acquisition, preprocessing, feature extraction, state estimation or thresholding, and finally, the delivery of feedback through a visual or auditory interface. This general framework forms the basis of the technical synthesis presented in the following subsections.

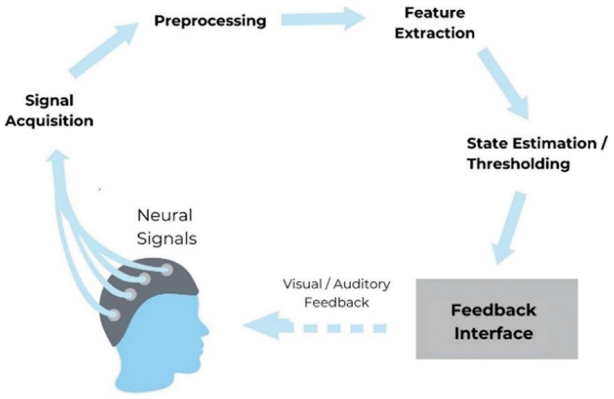


Fig. 2. General architecture of a closed-loop BCI-based neurofeedback system for working memory training

3.1. SIGNAL ACQUISITION MODALITIES AND HARDWARE CONFIGURATION

The most common signal acquisition modality in the reviewed studies was EEG. EEG-based neurofeedback systems were used in 19 out of 21 implementations [21-27, 29-31, 33-41]. Conversely, two studies employed fNIRS [28, 32]. This distribution suggests a strong dominance of EEG in neurofeedback studies of working memory based on BCI.

There was a high degree of heterogeneity in both EEG hardware configuration and electrode placement. Some studies used site-specific montages that focus on frontal or parietal areas (including Fz, Pz, Cz, F7, F3, F4, F8 and prefrontal electrodes Fp1 and Fp2) [27, 29, 30, 33-35, 37]. These placements are consistent with the frontoparietal networks that are constantly involved in the working memory processes. Other studies used a wider channel coverage, such as 8-channel systems [31], 14-channel devices [39], 16-channel portable platforms [35], and 64-channel high-density EEG systems [40], demonstrating a wide range of complexity in the acquisition of various systems.

A clear trend toward portable and easy-to-use EEG solutions is evident in the literature. Besides the traditional laboratory designs, other studies combined wireless devices, dry-electrode headbands, OpenBCI platforms, Emotiv systems, and smartphone-assisted interfaces [25], [26], [33], [35], [39]. This tendency indicates the growing interest in reducing the amount of required hardware and the improvement of the accessibility of neurofeedback programs. However, some of the studies had more organized clinical or laboratory designs, especially those that used multi-channel recordings, immersive conditions, or highly controlled training models [31], [40].

Comparatively, fNIRS provides a more region-specific hemodynamic monitoring approach, aimed at monitoring frontoparietal functional connectivity through hemoglobin oxygenation (HbO) measurements. Acevedo *et al*. [32] tracked the activities of the prefrontal region using a special sensor platform. Such systems were in contrast to the EEG implementations in terms of the focus on regional blood-oxygenation responses and not on oscillatory electrical activity.

Taken together, these results indicate that EEG is the primary acquisition modality of BCI-based working memory neurofeedback, and that fNIRS is used less and in more specific applications. The variability in channel density, electrode positioning, and the portability of hardware used in the EEG studies highlights the absence of an established standard for acquisition setup in the EEG domain.

3.2. FEATURE EXTRACTION AND SIGNAL PROCESSING STRATEGIES

Frequency-domain neural features were most commonly used for analysis. The summary of the distribution of these targeted features is provided in Fig. 3. As demonstrated, alpha-based strategies were the most used, then theta-based, ratio-based and sensorimotor rhythm (SMR) or band-specific strategies. Conversely, the features based on connectivity, entropy, and personalized system scores were only found in a limited number of studies.

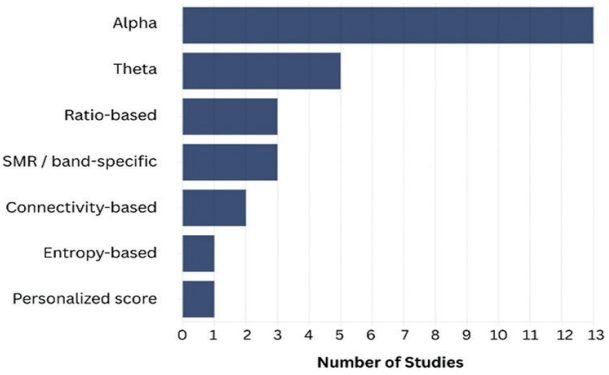


Fig. 3. Distribution of the feature extraction plans applied in BCI-based neurofeedback research on working memory. Note: There were studies that used more than once in the category of features; thus, the number of studies is less than the total frequency

The most common frequency-based protocols were alpha-based neurofeedback, fixed-band alpha, upper alpha, individualized alpha, and high-alpha targets [22], [24], [25], [30], [31], [33], [34], [35], [36], [41]. One of the interesting engineering trends in this subgroup was the application of individual spectral calibration. Instead of using fixed frequency bands only, various studies obtained the Individual Alpha Frequency (IAF)

or Peak Alpha Frequency (PAF) to customize neurofeedback targets [22], [24], [30], [41]. This implies that it is an attempt to explain the inter-individual variability in neural oscillations, as well as make feature extraction more specific.

The second most common pattern was that of theta-based and ratio-based features. Some of the systems were direct theta or combined measures (like theta/alpha or theta/low-beta ratios), indicating efforts to measure more dynamic changes related to attentional regulation and executive control [21], [24], [29], [38]. The use of ratio-based techniques is especially interesting as it combines the data of different spectral components, as opposed to using only a single spectral band. SMR and protocols based on motor imagery with trained bands at 12, 18, and 21 Hz were also reported [22], [23], [27].

Though frequency-based features were predominant, fewer systems used non-spectral or highly-derived features. HbO-based frontoparietal functional connectivity was extracted by HbO signals in the fNIRS in [28], and prefrontal activity scores were used in Acevedo *et al*. [32]. Suhail *et al*. [40] used a non-linear method by calculating real-time EEG sample entropy to produce an attention score. Furthermore, Yeo *et al*. [26] applied a subject-specific Brain Score that was optimized using a Stroop task. These studies suggest that connectivity-, complexity-, and personalized score-based strategies are starting to be used in addition to traditional band-power strategies.

Despite the dominance of frequency-based approaches, several signal-processing limitations remain relevant in BCI-based neurofeedback systems. These include low signal-to-noise ratio, nonlinear neural signal behavior, trade-offs between processing speed and model complexity, and identification limitations related to channel configuration, number of classes, and classification performance. In addition, although most of the reviewed studies relied on relatively conventional feature extraction strategies, AI- and machine-learning-based approaches, including deep learning, are receiving increasing attention in broader BCI research. These methods can improve feature representation and classification performance, as shown in deep-learning-based BCI implementations [42]. However, they also introduce challenges related to computational cost, interpretability, and real-time deployment.

Regarding the reported neural outcomes, a significant number of studies revealed a neural modulation of the target feature, including a higher alpha power, higher theta/alpha ratio, or stronger frontoparietal connectivity [21], [23], [24], [25], [28], [35]. Nevertheless, this feature modulation was not necessarily associated with the consistent changes in the working memory performance [30], [37], [39]. This suggests that although frequency-based feature extraction is still the predominant signal processing approach in present BCI-based neurofeedback, the connection between neural modulation and behavioral outcome is still heterogeneous across the sampled studies.

3.3. FEEDBACK ARCHITECTURES AND TRAINING PROTOCOLS

The most commonly used interface modality observed in the reviewed systems was visual feedback. Graphical interfaces, such as rotating balls, bars, puzzle pieces, score gauges and object-control games, were often part of the EEG-based neurofeedback systems [21], [24], [27], [36]. Other studies used more interactive or gamified interfaces, including a smartphone-assisted interface, Unity3D-based workspace, motor-imagery-cursor control, game based on apps, and 3D visual-arena interface [23, 25, 31-33, 35, 40].

The use of auditory feedback was less frequent, but it was also evident in several studies as the dominant feedback or as a component of a multimodal setup. These experiments used tones, music, waves or individual beeps as a means of communicating the feedback information [29, 30, 38, 41]. Audiovisual combinations were also used in some of the protocols [22, 30]. Shen *et al*. [34] directly compared visual and auditory neurofeedback and found no significant neurofeedback learning difference between the two groups. However, learners who succeeded in neurofeedback learning showed better neurofeedback updating across the two conditions.

The training schedules differed greatly among the studies. Others leaned more toward a short intensive protocol, which usually lasted three to eight days or one week of intense training [21, 24, 28, 29, 36]. Other studies utilized multi-week protocols (between three and ten weeks), where the sessions were offered once or multiple times a week [23, 25-27, 32, 33]. Some of the studies also included a follow-up assessment or booster session as a way of evaluating the long-term effects of the training [26, 28, 38].

There was significant variability in the within-session structures. Numerous EEG-based protocols split the training into repeated short blocks, each three to five minutes long with a short period of rest between them [24, 25, 34, 35, 36, [39]. Research that applied longer one to two-hour sessions was mainly done in traditional neurofeedback or rehabilitation facilities [22, 41]. The majority of EEG-based systems provided feedback in a continuous or near-real-time form. The fNIRS-based system used by Acedevo *et al*. [32] used delayed feedback, which shows the slower temporal nature of hemodynamic signals.

The synthesis of the reviewed studies shows that there is a high preference for visual screen-based neurofeedback interface and, simultaneously, there is the emergence of the tendency to use gamified and immersive interaction design. At the same time, the high level of heterogeneity in terms of training duration, the frequency of sessions, and the modality of feedback delivery indicates that there is no standardized framework of protocols in terms of training working memory using the BCI.

3.4. EXPERIMENTAL DESIGN AND CONTROL STRATEGIES

Most studies included some form of comparison condition, and these findings imply that controlled evaluation designs are fairly prevalent in neurofeedback research using BCI to study working memory. Sham neurofeedback and passive and no-training controls were the most commonly used control strategies. Seven studies [21, 24, 25, 27, 30, 36, 41] used sham-controlled designs. Another seven studies used passive or no-feedback control conditions, such as no-training groups, no-neurofeedback groups, or control groups who only underwent pre- and post-testing [23, 28, 29, 33, 34, 35, 38]. All 14 of these studies point to an increasing awareness of the necessity to differentiate between specific neurofeedback and general practice, as well as expectancy and time-related increases.

Fewer studies applied active comparison designs. These were behavioral training and no-training comparators [21], cognitive training and combined neurofeedback-cognitive training arms [24], treatment-as-usual rehabilitation situations [22], app-based active control with Tetris [32], and control conditions based on up-regulating randomly selected frequency bands [37]. Instead of a traditional sham, Accoto *et al*. [31] utilized an alternative condition design and compared varying degrees of virtual reality (VR) vividness with neurofeedback performance as a measure of how interface characteristics influence neurofeedback performance. These multi-arm or active-controlling methods are methodologically useful in that they assist in disentangling the neurofeedback effects due to general task engagement, interface novelty or parallel cognitive stimulation.

Regardless of the popularity of the use of control groups, the methodological rigor was not consistent across the studies. Other protocols used powerful sham designs based on non-contingent or pre-recorded feedback [25, 36, 41], whereas others used open-label waitlist controls or passive comparisons [26]. Suhail *et al*. [40], on the other hand, did not involve a sham or active control group, which the authors stated as a limitation. This control design difference affects the interpretability of the reported effects, particularly in studies where practice effects, expectancy effects or familiarity with the interface might have affected the results.

Each type of control strategy has its own advantages and limitations. Sham-controlled designs are more rigorous and help to isolate neurofeedback-specific effects but they are difficult to implement, especially when maintaining participant blinding. No-training or passive controls are simpler to implement but are more prone to expectancy effects and fail to explain task engagement comprehensively. Active control designs provide a more realistic comparison and can be used to differentiate the effects of neurofeedback and general cognitive stimulation, but they can also add more confounding variables because of the variations in task demands.

3.5. REPORTED EFFECTIVENESS ON WORKING MEMORY

The results of the reviewed studies point to the fact that BCI-based neurofeedback could lead to the improvement of the working memory performance, even though the reported effects were not consistent in terms of protocols, outcome measures, and populations. In order to give an overview of the reported neural modulation, working memory improvement, effects of cognitive transfer, and follow-up retention at the study level, the outcome matrix is provided in Fig. 4. To ensure consistency in the interpretation of Fig. 4., we have used the same coding scheme across the studies, so then the outcomes of neural-modulated working memory improved. Transfer effects (defined as cognitive effects beyond working memory) were coded *Yes* when neurofeedback produced better results, *Mixed* when they were more inconsistent or subgroup-specific, *No* when neurofeedback had no effects, and *Not reported* when they were not reported in a clear way.

A number of studies have found working memory gains that are usually manifested as higher accuracy and/or lower error rates in tasks like n-back and backwards digit span, and in some cases, an increase in visuospatial working memory paradigms. The articles that reported working memory improvement used n-back performance [21, 22, 28, 35, 38, 41], backward digit span [25], and other working memory-related measures, including Corsi or visual working memory accuracy measures [36]. These results indicate that in specific training and targeting parameters, neurofeedback can produce quantifiable working memory benefits.

Meanwhile, working memory results were often confounded, task-related or individual learning achievement-based. According to Gomez-Pilar *et al*. [23], the authors found improved memory-related domains more consistently than others, and their results indicated a mixed profile, and not a homogenous enhancement of working memory. Yeo *et al*. [26] did not see any overall improvement in the full sample, but subgroup patterns (e.g. sex-dependent effects) indicated heterogeneous responsiveness. Shen *et al*. [34] also reported similar results, finding the greatest effects of working memory updating related to the benefits of the participants who managed to learn to control the neurofeedback target. By contrast, small and selective (as opposed to generalized) changes in working memory indices (like a few improvements in specific n-back components) were reported by Accoto *et al*. [31]. These trends indicate that there is significant between-study and within-study variability, showing that working memory effectiveness can vary as per the protocol design, sensitivity of the outcomes, and the ability of the participants to learn how to control the specific target neural feature.

Several studies notably demonstrated that neural modulation is not necessarily converted into working memory improvement. Other studies were able to show the manipulation of the desired neural activities with no

reported behavioral working memory performance. In one example, Chikhi *et al*. [37] found that the target frequencies were modulated but there were no differences in the improvement of working memory according to the conditions, referring to practice-related or non-specific performance increases. Diotaiuti *et al*. [39] reported an increase in alpha amplitude, but no working memory improvement beyond practice effects.

Similar neural changes (e.g., connectivity differences) were also demonstrated by Nawaz *et al*. [33], but behavioral working memory performance increased equally in both neurofeedback and control groups, implying that the observed working memory change could not be estimated as being caused by neurofeedback in particular.

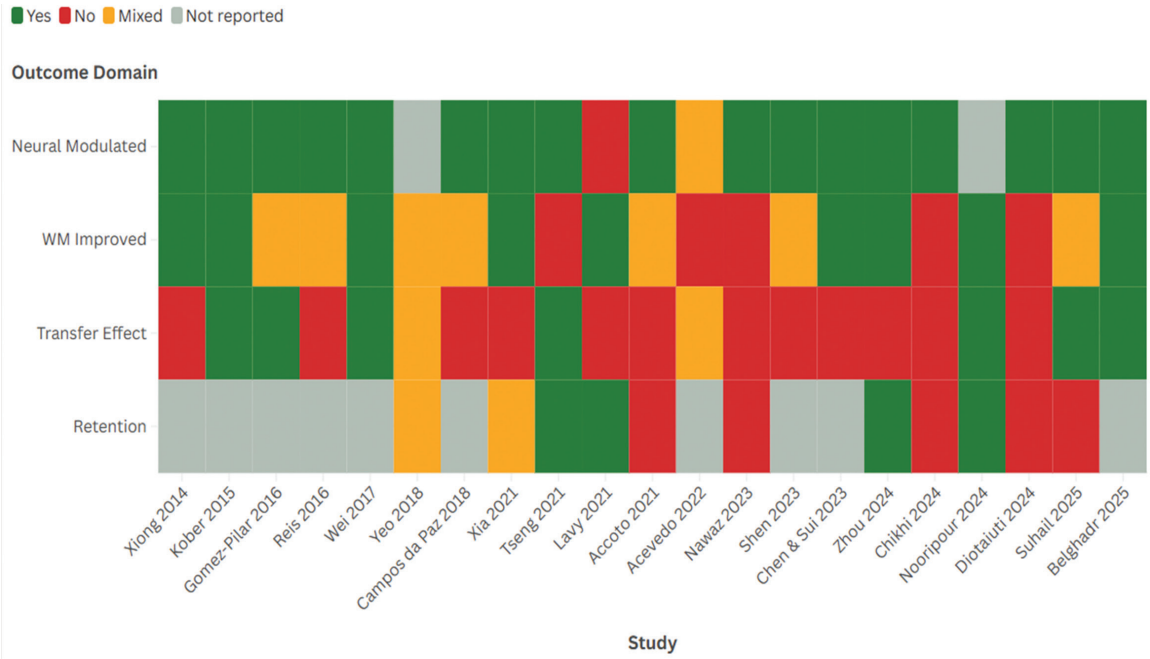


Fig. 4. Outcome matrix summarizing the reported neural and cognitive effects in BCI-based neurofeedback studies for working memory. Green indicates a positive reported effect, red indicates no significant effect, orange indicates mixed or subgroup-dependent findings, and gray indicates that the outcome was not assessed or was not clearly reported

Moreover, other studies have found a positive effect in other cognitive domains without an equivalent increase in working memory, including Tseng *et al*. [29]. They found an advantage in episodic and semantic memory but not working memory. The evidence basis is encouraging, although imbalanced. Although several studies report working memory benefits, the effects differ according to the target features, training parameters, population and outcome measures, while the extent to which measurable neural modulation can take place in the absence of evident working memory gains has been reported in many studies. It is important to note that such variability highlights the necessity of more standardized choices of outcome, the better reporting of intervention-specific effects compared to controls, and the systematic assessment of people benefiting most of all of neurofeedback-based working memory training.

4. DISCUSSION

In this part, the key findings of the systematic review are interpreted concerning system design, evaluation practice, and reported effectiveness. It also addresses the implication of these results related to future BCI-based neurofeedback research on working memory that focuses on better methodological reliability, the rigor of validation and practical system development.

4.1. CURRENT CHALLENGES AND RESEARCH OUTCOMES

The reviewed literature shows that EEG-based architectures have been the dominant platform for working memory neurofeedback, most commonly implemented with visual feedback interfaces and frequency-domain signal processing. The alpha, theta, SMR, and ratio-based features are the most popular neural targets that have been developed based on the practical advantages of the spectral measures in real-time application [21, 22, 24, 33, 41]. Some studies have also employed individualized calibration techniques, such as IAF-based targeting or PAF-based targeting, with a greater sensitivity to inter-individual variations in neural oscillations [22, 24, 30, 41]. Even though such frequency-domain features still prevailed, a smaller number of studies have examined alternative approaches such as sample entropy and fNIRS-based hemodynamic measurements [28, 32, 40]. The combination of EEG

and fNIRS modalities offers complementary advantages in BCI systems. EEG captures rapid neural dynamics due to its high temporal resolution, while fNIRS provides better spatial localization and is less sensitive to electrical noise. Together, they can improve signal reliability and provide a more complete representation of neural activity, which may enhance classification performance and system robustness. Feedback design is becoming more diversified, and some systems started to go beyond mere visual displays to more interactive, game-like, and immersive experiences [23, 31-33, 35].

The heterogeneity of the participant groups that were utilized in the reviewed experiments is another factor that results in the variability found among the studies. The chosen studies have covered a wide range of diverse groups of participants, such as healthy young adults, university students, older adults, athletes, and clinical populations like stroke patients, stroke patients with mild impaired memory (MCI), and students with learning disabilities. The differences in underlying cognitive ability, neural plasticity and learning ability could determine the differences in responsiveness to neurofeedback training. Therefore, the variations in the characteristics of the participants can partly explain the reason why some studies have claimed to have strong improvements in working memory performance, and some studies have indicated less significant or task-specific effects.

Simultaneously, methodological rigor varied across the reviewed studies. Although there were numerous studies that used control groups, passive or no-training controls were still frequent, and more powerful sham or active comparison designs were used less often [21, 24, 25, 27, 30, 33, 41]. Most studies prioritized cognitive and neural outcomes, and fewer studies reported usability evaluation and system-oriented assessment. Several challenges remain in the practical implementation of BCI systems, including low signal-to-noise ratio, nonlinear signal behavior, trade-offs between processing speed and model complexity, and limitations in classification performance and generalization. These issues have been widely discussed in system-level BCI reviews [43], and are also evident in practical application-oriented implementations [44].

Specifically, differences in responsiveness to neurofeedback, commonly referred to as BCI illiteracy [45], can contribute to the effectiveness of working memory neurofeedback systems. Prior research indicates that some users might have problems with reliable BCI control because of variations in their neural patterns, cognitive tactics or the compatibility between the system and the user [45]. Meanwhile, the notion of BCI illiteracy has been subjected to critical scrutiny, with some scholars claiming that performance constraints might be the phenomenon that points to the flaw in the design of the BCI system, rather than an intrinsic performance constraint [46].

Such observations indicate that more adaptive and personalized neurofeedback systems are needed to better accommodate user variability. Meanwhile, it would be easier to compare study results when there is more uniformity in the way that the signals are obtained, features described and results assessed. Neural pattern and learning response differences are also one of the major challenges, and it is important to note that user-specific calibration and system adaptation are also important. Multimodal and data-driven methods are also under investigation, but their implementation is not yet easily available. Further research is required, particularly by using suitable control conditions, longer follow-ups, etc., in order to get a clearer picture of the true efficacy of these systems. These considerations form the basis for the design principles presented in the next section.

4.2. GUIDELINES TO FUTURE STUDIES ON BCI-BASED NEUROFEEDBACK AND WORKING MEMORY

Continuing from the design patterns, evaluation constraints and effectiveness results outlined regarding RQ1-RQ3, future research should have a more uniform method for developing and validating BCI neurofeedback systems applied to working memory. The literature review has found several common strengths, including the extensive use of EEG-based architectures and frequency domain features of the neural signal, which are more suited to real-time implementation.

To overcome these hurdles, Fig. 5. gives a list of recommended design and validation rules based on the discoveries of the current review. These guidelines are intended to provide a systematic guide to upcoming BCI-based neurofeedback studies that concern working memory, with the objective of increasing methodological reliability and allowing more interpretable comparisons across experimental procedures.

The proposed guidelines are divided into three interconnected elements, as shown in Fig. 5. The former focuses on system design, which involves signal modality selection, feature extraction strategy selection and individualized calibration in the event of suitability. The second element deals with feedback and protocol design, with the emphasis being on the modality of the interface, the dosage of the session, the organization of the training blocks, and the fact that there is a need to control user engagement and fatigue over repeated training sessions. The third element is related to validation and outcome assessment and emphasizes the significance of sham or active control conditions as well as the use of more standardized working memory measures, the simultaneous reporting of neural and behavioral results, and the follow-up evaluation being longer than the immediate post-test.

These three elements exist in sustained system refinement cycle, whereby the initial design decisions affect the protocol structure, which subsequently dictates the amount of rigor that the validation needs to achieve.

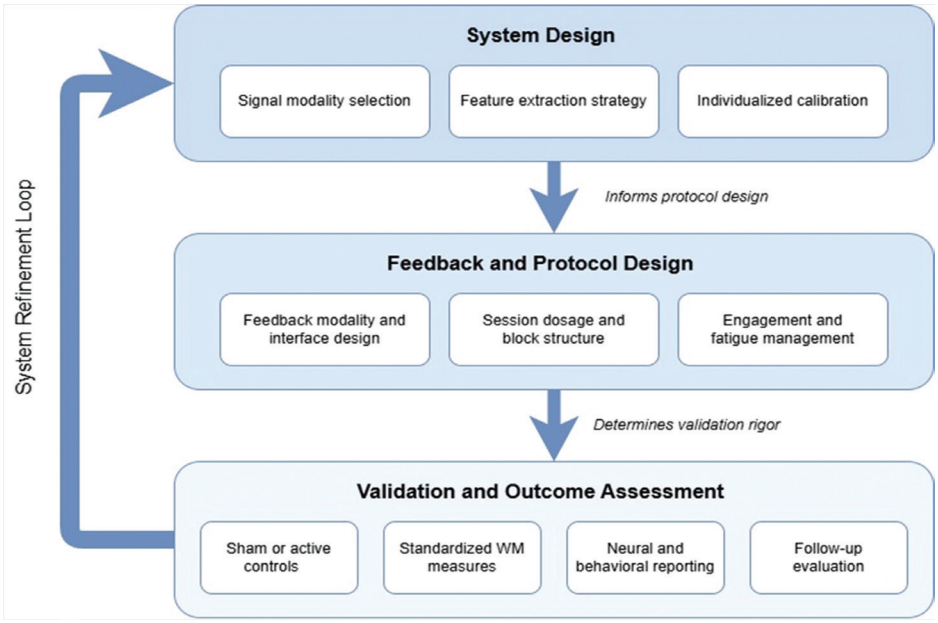


Fig. 5. Proposed design and validation guidelines for future BCI-based neurofeedback studies targeting working memory, synthesized from the technical, methodological, and outcome patterns identified in the present systematic review

Evidence from studies outside the included set further supports the need for such guidelines. General reviews on neurofeedback and meta-analytic research have indicated that α-based programs might be especially pertinent to working memory enhancement, but they have also identified long-term issues like the heterogeneity of responder profiles and methodological non-standardization. Also, studies using real-time connectivity-based neurofeedback in conjunction with functional magnetic resonance imaging (fMRI) have produced complementary evidence on the function of the frontoparietal network modulation in working memory. Even though these systems are no longer the focus of the current review because they use non-portable EEG - or fNIRS -based BCI systems, the results support the necessity of better neural target selection, increased validation designs, and the systematic follow-up evaluation of future studies [10, 47, 48].

Taken together, these recommendations are aimed at being used as a more practical guide to improve the consistency of the designs, methodological rigor and comparability of future studies involving neurofeedback based on BCI. They also justify the continued research directions on adaptive and user-oriented BCI applications, such as neurofeedback-based methods of cognitive rehabilitation training that customizes training with the help of EEG-based feedback [49].

4.3. LIMITATIONS OF THE REVIEW

There are several limitations that should be considered in the interpretation of the findings of this systematic review. To start with, the literature search was limited to the English-language articles included in the four selected databases, i.e., Scopus, Web of Science, PubMed, and IEEE Xplore. As a result, other relevant studies published in other languages, available in other databases or in other grey literature might have been excluded.

Second, there is the significant methodological heterogeneity of the studies under consideration. Differences in signal modality, feature extraction goals, training time, feedback form, control variables and control conditions and working memory evaluation instruments barred cross-study comparisons. Despite the current increase in research activity in the field, the field is still methodologically uneven. Heterogeneity was also observed in the process of screening the studies as a significant proportion of the retrieved records could not be included because of the lack of closed-loop neurofeedback implementation, emphasis on other areas of cognitive functioning, or a lack of methodological description. Although this heterogeneity indicates the state of current development in the field, it also limits the possibility of broader generalizations on effectiveness.

Lastly, publication bias is not to be ruled out, as is typical in the still developing fields of research. Studies that record good cognitive or neurophysiological results might have a better chance of being published compared to those studies that show null results or negative results.

5. CONCLUSION

This systematic review synthesized the information available on the design, evaluation, and effectiveness of BCI-based neurofeedback systems of working memory. The analyzed literature demonstrates that under certain conditions, BCI neurofeedback, especially EEG-based systems using frequency-domain features, can be used

to elevate working memory performance. Regardless, the field is still typified by significant methodological diversity in signal modality, feature extraction and feedback design, control strategy and result evaluation. Another trend that is repeated in the literature is that the successful induction of the desired neural property does not always correspond to any significant cognitive change, which implies that there is not a consistent relationship between technical and behavioral measures. Passive control conditions remained widespread, and follow-up assessments were relatively rare, limiting conclusions on specificity and long-term retention. In order to mitigate these concerns, the current paper suggests a list of design and validation guidelines that can be used in upcoming research. These guidelines can help improve comparability and rigor in future working memory neurofeedback studies based on BCI by promoting clarity in their choice of features, protocol consistency, control, and the better incorporation of neural, behavioral, and follow-up data.

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DECLARATION OF THE USE OF AI TOOLS

The authors used ChatGPT (OpenAI) strictly for language polishing and grammatical correction during the preparation of this manuscript. The core research, data analysis, and final content are entirely the original work of the human authors. All authors reviewed the final text and take full responsibility for the manuscript's integrity and accuracy.

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