The Application of Wearable Electroencephalogram-Based Neurofeedback in Attention-Deficit/Hyperactivity Disorder: a Brain-Computer Interface Solution for Enhancing Attention

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Abstract: Wearable electroencephalogram (EEG)-based neurofeedback has emerged as a promising non-pharmacological approach for improving attention and managing core symptoms of attention-deficit/hyperactivity disorder (ADHD). By providing immediate visual or auditory cues tied to neural activity, individuals can learn to self-regulate specific brain rhythms associated with focus, impulsivity, and hyperactivity. Recent technological advances in electrode design and artifact mitigation now allow for practical, user-friendly solutions in everyday settings, including home and school environments. Furthermore, integrating real-time motion tracking with EEG recording enhances data reliability, particularly for children who tend to be restless during training. Personalized protocols that tailor the intervention to individual EEG profiles have shown potential in increasing the proportion of successful learners. In addition, combining EEG neurofeedback with other modalities and complementary behavioral strategies may further strengthen therapeutic outcomes. This review explores the current state, challenges, and prospects of wearable EEG neurofeedback for ADHD.

1 INTRODUCTION

Attention-deficit/hyperactivity disorder (ADHD) is a common neurodevelopmental disorder, affecting approximately 5% of children worldwide, often leading to decreased academic performance, impaired social interactions, and reduced quality of life (Lansbergen et al. 2011). Traditional therapeutic methods, such as pharmacological treatment and behavioral interventions, have demonstrated efficacy to some extent, yet frequently come with adverse side effects and inconsistent long-term effectiveness (Enriquez-Geppert et al. 2019). Thus, exploring safe, non-invasive, and sustainable alternative interventions is of critical importance. In recent years, the rapid advancement of wearable EEG technology has opened new avenues for neurofeedback therapy. Neurofeedback techniques collect real-time EEG signals and translate specific frequency-band activity into intuitive feedback, enabling individuals to conduct self-regulation training in natural environments and thereby improve their attentional state (Flanagan & Saikia 2023). This brain–computer interface-based intervention, utilizing affordable and portable EEG devices, overcomes traditional laboratory constraints and can enhance patient engagement and adherence in real-world settings such as home and school (Zamora Blandón et al. 2016). Current studies indicate that targeted modulation of EEG parameters—for example, reducing theta-wave power while enhancing beta-wave activity—can improve attention control in patients with ADHD (van Doren et al. 2019). Moreover, several systematic reviews and meta-analyses have demonstrated additive therapeutic effects when EEG neurofeedback is combined with pharmacological treatments, particularly in improving core symptoms of ADHD (Lin et al. 2022). This non-invasive intervention not only offers novel therapeutic approaches in clinical practice but also lays the groundwork for personalized and remote-monitoring strategies in future treatment paradigms (Emish & Young 2024). Furthermore, individualized neurofeedback programs guided by quantitative EEG (QEEG) techniques allow tailored training strategies based

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on each patient's unique EEG characteristics, potentially leading to more targeted improvements in attention deficits and paving the way for personalized medical care (Arns et al. 2012). This review systematically examines the latest advancements in wearable EEG-based neurofeedback for ADHD treatment, emphasizing its safety, efficacy, and long-term sustainability in enhancing attention while reducing hyperactive and impulsive symptoms. By integrating findings from randomized controlled trials, meta-analyses, and open-label studies, this paper not only evaluates the clinical potential of EEG neurofeedback in treating ADHD but also provides theoretical guidance for designing future individualized intervention strategies.

2 CURRENT RESEARCH METHODS: COMPARATIVE ANALYSES AND IMPROVEMENT RECOMMENDATIONS

Recent EEG-neurofeedback research on ADHD has employed a diverse range of study designs, spanning rigorous randomized controlled trials (RCTs) with double-blind placebo or sham-feedback conditions to more flexible open-label investigations (Lansbergen et al. 2011, Enriquez-Geppert et al. 2019, Garcia Pimenta et al. 2021). While the stringent RCT, double-blind approach can minimize expectancy bias, its implementation often requires considerable logistical resources and is not without ethical implications. Consequently, several studies use single-blind or open-label frameworks, acknowledging that open-label designs, though less cumbersome, remain prone to heightened placebo effects (Zamora Blandón et al. 2016, Arns et al. 2012, Barth et al. 2021). Participant selection and randomization strategies also vary: some investigations focus solely on school-aged children, whereas others enroll adolescents or adults. Notably, these choices influence outcomes because factors such as medication status, ADHD subtypes, and co-occurring conditions can moderate training efficacy (Zamora Blandón et al. 2016, Arns et al. 2012). These divergences further complicate subsequent meta-analyses, given the heterogeneous methods that mix different age groups and symptom profiles (Barth et al. 2021). Moreover, sample sizes in EEG-neurofeedback trials for ADHD are typically modest, undermining statistical power when evaluating group-level changes (van Doren et al. 2019). Many researchers thus advocate multi-center collaborations or data-sharing initiatives to enlarge pooled datasets and enhance result generalizability. In terms of analysis, repeated-measures ANOVAs and paired t-tests are commonly employed to compare baseline and post-training improvements. However, machine learning algorithms are increasingly being utilized to classify subtle EEG patterns associated with ADHD (Chauhan & Choi 2023, Yaacob et al. 2023). Such approaches are well-suited for capturing individualized response trajectories and detecting potentially overlooked brain-signal nuances. By moving beyond mere group-level comparisons, these emerging methods allow clinicians to account for personal brain signatures, thereby advancing the prospects for precision medicine in ADHD. Overall, while research methodology is strengthening, further standardization of both design and analysis is crucial to firmly establish neurofeedback's clinical effectiveness and ensure cross-study comparability.

Reported findings indicate that EEG neurofeedback can reduce core ADHD symptoms—particularly inattention and impulsivity—across multiple investigations (Lansbergen et al. 2011, Garcia Pimenta et al. 2021). Nonetheless, these apparent benefits should be interpreted judiciously. A persistent issue involves participant generalizability: although some individuals ("learners") readily acquire and maintain targeted EEG modulation, others ("non-learners") show negligible training effects (Garcia Pimenta et al. 2021, Barth et al. 2021). Such disparities can distort group-level assessments of neurofeedback outcomes and may reflect differences in reward sensitivity, baseline brain patterns, or motivation. Further complicating the landscape, EEG signals are notoriously vulnerable to artifacts arising from muscle tension, eye blinks, or body movement, especially among children whose restlessness may substantially degrade signal quality (Zamora Blandón et al. 2016, Pei et al. 2022). These artifacts can mask meaningful neuronal patterns, diminishing the reliability of real-time feedback. Differences in control conditions also matter. Some studies employ sham feedback or placebo interventions; others rely on waiting-list controls or established cognitive training regimens; and a few compare neurofeedback directly with stimulant medications. Because each control condition invokes distinct nonspecific influences—from expectancy to coaching—synthesizing results remains challenging. Indeed, comparing data across heterogeneous designs demands considerable caution and underscores the pressing need for consensus protocols. In response, scholars have proposed expanding sample sizes and enhancing methodological uniformity to minimize random variation and mitigate nonspecific confounds (van Doren et al. 2019, Barth et al. 2021). Additionally, advanced data-processing pipelines featuring robust artifact rejection can better isolate genuine brain-signal changes. Another recommended strategy involves personalizing neurofeedback to each participant's QEEG profile (Garcia Pimenta et al. 2021, Barth et al. 2021). For instance, individuals with abnormal theta/beta ratios might benefit from frequency-specific training, whereas those displaying atypical slow cortical potentials could pursue alternative protocols. This tailored approach aims to address the "non-learner" challenge by aligning the feedback strategy with each child's neurophysiological profile, potentially increasing the likelihood of consistent brain-signal modulation and clinically meaningful outcomes.

3 EQUIPMENT TECHNOLOGY AND SIGNAL ACQUISITION: INNOVATIONS AND OPTIMIZATIONS

Rising demand for at-home ADHD neurofeedback protocols has accelerated the development of convenient, user-friendly EEG headsets (Flanagan & Saikia 2023). Typically, these consumer-grade devices incorporate fewer electrodes, simplified signal amplifiers, and faster setup procedures. Because families can administer sessions independently, children can receive more frequent and potentially more ecologically valid training. However, such portable gear may be especially susceptible to electromagnetic noise and head-motion artifacts if a child fidgets during lengthy sessions. Consequently, stable electrode contact and low impedance remain crucial. Conventional "wet" electrodes using conductive gel offer strong coupling and low resistive noise, but require extensive preparation time and post-session cleanup, potentially hindering daily home use. By contrast, "dry" electrodes promise near-instant application yet often exhibit higher contact impedance, risking signal attenuation or drift over repeated movements (Zamora Blandón et al. 2016, Pei et al. 2022). A practical compromise has emerged in "semi-dry" or "half-wet" electrodes that partially maintain moisture via a minimal reservoir of saline or hydrogel. These designs can markedly reduce setup time while avoiding the dryness-induced noise typical of conventional dry electrodes. Notably, pre-gelled (PreG) electrodes—packaged with a stable hydrogel—have gained attention for their quick application and robust signal fidelity comparable to standard wet electrodes (Pei et al. 2022). Because ADHD training sessions may exceed 20–30 minutes, consistent user comfort is also critical. If electrode pressure or scalp friction causes irritation, data quality and participant compliance can deteriorate. Among pediatric populations, discomfort or time-consuming routines may undermine adherence. Consequently, hardware researchers emphasize ergonomics, ensuring that headbands or caps apply minimal scalp pressure while maintaining adequate electrode-skin contact. Although most consumer EEG solutions feature lower electrode density than their laboratory-grade counterparts, they show promise for cost-effectively scaling neurofeedback interventions to larger ADHD cohorts in realistic environments.

Beyond hardware innovations, advanced EEG preprocessing is vital for maximizing data reliability, particularly in dynamic or home-based settings. Conventional methods include band-pass filtering (e.g. 1–45 Hz) to remove low-frequency drifts and line noise, followed by artifact correction. Techniques such as independent component analysis (ICA) excel at isolating ocular or muscle artifacts from genuine neural oscillations, yet they typically rely on offline post-processing and cannot fully safeguard real-time feedback loops from abrupt signal contamination. Accordingly, recent research prioritizes integrated artifact detection that operates continuously, enabling immediate suppression of spurious signals (Zamora Blandón et al. 2016, Pei et al. 2022, Yaacob et al. 2023). One promising strategy involves merging inertial measurement unit (IMU) sensors with EEG data: headsets equipped with accelerometers or gyroscopes can track head motion and automatically discount intervals of abrupt movement, helping preserve feedback fidelity. Given that ADHD participants often exhibit restlessness, such automated artifact removal contributes to more reliable training. In addition, the field increasingly advocates standardization in hardware design and data formatting. Drawing on precedents in MRI and fNIRS research, many EEG practitioners endorse Brain Imaging Data Structure (BIDS)-like guidelines that outline consistent naming conventions, metadata files, and directory architectures. Aligning with these protocols reduces confusion when merging datasets from multiple sites and bolsters large-scale meta-analyses. For example, if certain PreG electrode setups or real-time motion filters become widespread, researchers relying on BIDS-based references can compare data more systematically. In essence, the intersection of refined electrode technology, continuous artifact mitigation, and standardized data practices underpins a more robust, scalable, and clinically viable framework for EEG-based neurofeedback—bridging the gap between controlled lab studies and everyday ADHD interventions in schools or homes.

4 CROSS-DISCIPLINARY INTEGRATION AND MULTIMODAL DATA FUSION IN NEUROFEEDBACK APPLICATIONS

Traditional ADHD assessments have predominantly relied on behavior rating inventories (e.g. parent- or teacher-report scales) and the continuous performance test (CPT). Although instrumental for diagnostic screening and follow-up, these measures can suffer from subjective biases and limited ecological validity (Wiebe et al. 2023). Consequently, there is growing interest in augmenting standard assessments with objective neurophysiological markers, especially EEG. For example, a VR-based CPT can situate participants in a quasi-realistic environment replete with distractors, while simultaneously recording EEG data to detect cortical oscillation deviations at moments of inattention or impulsivity (Wiebe et al. 2023). Such integrated methods can better identify ADHD subgroups that fail to filter out irrelevant stimuli, thereby enhancing diagnostic precision. When self-reports yield conflicting or unclear outcomes, corresponding EEG signatures may clarify the underlying attentional deficits. In both clinical and research applications, integrating EEG into ADHD assessment confers dual benefits: it provides continuous, real-time neural activity to supplement subjective rating scales, and it enables objective tracking of therapy responsiveness—whether from medication, behavioral interventions, or neurofeedback. Researchers have noted that stable shifts in fronto-central EEG rhythms frequently accompany improvements in daily functioning. Conversely, if post-treatment rating scales suggest progress but EEG metrics remain largely unchanged, clinicians might investigate whether external biases inflated subjective judgments. Thus, combining qualitative and quantitative insights can yield a more comprehensive and trustworthy view of patient progress. Early results from integrated protocols show that repeated self-regulation of specific EEG rhythms—guided by continuous neural feedback—may help participants sustain improvements beyond training sessions. Observing these gains in more naturalistic tasks, such as VR-based or real-world scenarios, reinforces confidence in the potential generalizability of EEG-based interventions. However, broader clinical adoption will require greater uniformity in VR task designs, outcome metrics, and data-analytics pipelines.

From a human–computer interaction (HCI) perspective, neurofeedback systems must provide feedback that meaningfully engages users with ADHD without overloading their cognitive capacity. Virtual reality (VR) offers a promising solution: immediate visual and auditory cues in an immersive environment can promote active participation. Preliminary studies suggest that integrating VR into EEG neurofeedback training can boost user motivation and sustain interest, potentially reducing dropout rates (Cho et al. 2004). Designing such systems demands attention to interface clarity, adjustable task difficulty, and minimal latency to ensure tight coupling between neural events and on-screen feedback. On a broader scale, multimodal approaches that combine EEG with functional near-infrared spectroscopy (fNIRS), eye-tracking, or peripheral physiological measures (e.g. heart rate) are becoming increasingly prevalent (Emish & Young 2024, Chen et al. 2024). Each modality contributes distinct information—fNIRS reveals cerebral hemodynamics in the prefrontal cortex, eye-tracking uncovers gaze shifts to irrelevant stimuli, and heart-rate variability indicates arousal or stress levels. Collectively, these signals yield a more holistic understanding of ADHD's diverse manifestations. Nonetheless, researchers must address synchronization issues due to varying sampling rates or temporal resolutions, highlighting the need for unified triggers, shared reference frames, and integrated software frameworks. Another obstacle lies in the absence of consistent standards for multimodal setups, including recommended electrode or emitter placements and validated data fusion algorithms. Following the BIDS initiative, experts are championing universal protocols specifying metadata formats, data-collection timing, and file structures for combined EEG–fNIRS–eye-tracking recordings (Pernet et al. 2019, Chen et al. 2024). Once established, such guidelines can strengthen data quality, reproducibility, and cross-laboratory collaboration. Ultimately, refining these multimodal neurofeedback systems will depend on interdisciplinary partnerships among neuroscientists, engineers, clinicians, and HCI specialists. Future platforms that seamlessly integrate multiple biometrics, adapt training dynamically in real time, and maximize ecological validity may prove instrumental in optimizing ADHD interventions and expanding their clinical impact.

5 CONCLUSION

Advances in wearable EEG neurofeedback for ADHD have offered new avenues for improving attentional regulation and addressing core symptoms such as inattention, hyperactivity, and impulsivity. Across various studies, advancements in device design—ranging from PreG and semi-dry electrodes to sophisticated artifact-rejection algorithms—have led to greater convenience and reliability in data acquisition. By reducing setup time and enhancing comfort, these developments aid consistent user adherence, a critical requirement given the need for repeated neurofeedback sessions. Furthermore, home-friendly EEG systems are increasingly recognized for their ecological validity, as children and adolescents often respond more naturally in familiar day-to-day environments than they would in clinical laboratories. While many trials report encouraging outcomes—particularly reductions in inattention and impulsivity—findings must be viewed with caution due to methodological disparities and limited sample sizes. Notably, a recent meta-analysis focusing on self-reported outcomes found no significant advantage of neurofeedback over control interventions on core ADHD symptom ratings (Fan et al. 2022). The heterogeneity of control conditions further complicates the extraction of firm conclusions. Additionally, the phenomenon of "learners" versus "non-learners" underscores substantial inter-individual variability. Some participants master EEG self-regulation with relative ease, whereas others show negligible change in their cortical rhythms or behavioral measures. For researchers, pinpointing why some individuals respond more favorably than others remains a key challenge. One potential answer lies in tailoring training protocols according to each participant's QEEG profile. Although these personalized approaches have demonstrated promise, larger-scale and multi-center studies are needed to systematically assess their superiority over "one-size-fits-all" methods.

On the technical side, real-time artifact detection has emerged as a vital component for ensuring robust feedback loops. By incorporating IMUs into wearable headsets, clinicians can swiftly filter out data segments compromised by motion or muscle activity. This integration of additional sensors not only preserves data quality but also aligns well with modern trends in multimodal neuroscience research. Synchronizing these signals, however, requires carefully harmonized hardware/software solutions as well as shared standards, analogous to the BIDS initiative. Although efforts toward such standardization are ongoing, more concerted cross-disciplinary collaborations—spanning neuroscience, engineering, data science, and clinical practice—could rapidly accelerate the refinement of multimodal neurofeedback frameworks. From a clinical standpoint, combining EEG neurofeedback with psychosocial or behavioral therapies may bolster overall treatment outcomes, particularly if parents and teachers remain engaged and supportive. Early evidence suggests that such integrated interventions can yield improvements not only in core ADHD symptoms but also in related behavioral or cognitive domains (Luo et al. 2023). Nonetheless, further validation via randomized, multi-center trials is crucial to solidify claims of lasting therapeutic benefit. Another avenue involves bridging neurofeedback with psychopharmacology. Preliminary meta-analyses indicate that neurofeedback may act synergistically with stimulant medications by either lowering the required dosage or complementing existing regimens (Lin et al. 2022). More extensive comparative-effectiveness studies should clarify the longevity and relative efficacy of these combination strategies.

In sum, wearable EEG neurofeedback for ADHD has reached a notable inflection point: hardware miniaturization, improved electrodes, and advanced machine learning techniques have converged to create systems that may soon become routine in both clinical and home settings. Still, critical challenges loom. Researchers must resolve inconsistencies in outcome measures and refine best-practice protocols for open-label and blinded studies alike. Concurrently, the field should prioritize larger sample sizes, standard data formats, and real-time noise mitigation to ensure replicable, high-quality findings. Ultimately, by combining technical ingenuity with robust methodological design, EEG neurofeedback stands poised to advance from an emerging adjunctive therapy to a mainstay intervention for ADHD—one that can be flexibly adapted to individual neurophysiological profiles and seamlessly integrated into daily life.

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