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# *Advances in the Application of Consumer-Grade Electroencephalography (EEG) Headbands to Attention-Training Games (2019–2025)*

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***Abstract.*** Attention-deficit/hyperactivity disorder (ADHD) has a global prevalence of approximately 5.3–7% among school-age children. Although traditional central nervous system stimulants are practical, adverse effects such as nausea, appetite suppression, sleep disturbances, and growth retardation have motivated increasing interest in digital therapeutics. This review synthesizes evidence from 38 empirical studies published between 2019 and 2025, focusing on hardware advancements, game design, algorithmic approaches, and outcome metrics related to consumer-grade EEG headbands. The quality of evidence is assessed using the PRISMA framework. The findings show: (1) the Muse and NeuroSky series dominate the market; dry-electrode channel counts have increased from 2 to 8 leads, with sampling rates up to 1 kHz; (2) training games predominantly employ Go/No-Go, n-back, and racing feedback paradigms, with an average of eight sessions producing significant improvements on Continuous Performance Tests (CPT) (Hedges g = 0.42); (3) randomized controlled trials (RCTs) of theta/beta ratio neurofeedback demonstrate efficacy comparable to methylphenidate, with effects maintained over 6–12 months. In summary, consumer EEG devices present benefits in terms of portability, reduced adverse effects, and accessibility for at-home use; however, limitations in current evidence stem from small sample sizes, inadequate blinding procedures, and a lack of personalized intervention strategies. Future work should pursue multicenter RCTs and integrate AI-driven adaptive algorithms and wearable sensing to enable plug-and-play, personalized digital therapeutics.

***Keywords:*** Consumer-grade EEG, ADHD, attention training, neurofeedback, serious games

## 1. Introduction

Attention-deficit/hyperactivity disorder (ADHD) has a global prevalence of approximately 5.3–7% among school-age children, with core symptoms of sustained inattention, impulsivity, and hyperactivity [1]. While central nervous system stimulants like methylphenidate demonstrate efficacy, frequently observed adverse effects encompass nausea, appetite reduction, sleep disruption, and growth deceleration [2], which can undermine adherence among parents and adolescents. Portable electroencephalography (EEG) headbands are relatively low-cost and easy to wear,

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providing a promising pathway for home-based digital therapeutics [3]. This paper provides the initial systematic synthesis of 38 empirical studies conducted between 2019 and 2025 within this domain. The synthesis is structured around four key dimensions: hardware advancements, game paradigms, algorithmic approaches, and clinical efficacy. This framework aims to offer evidence-based guidance for future clinical and industrial endeavors.

## 2. Research progress and evidence appraisal for consumer-grade EEG interventions in ADHD

### 2.1. Hardware platform evolution

Since 2020, mainstream devices have evolved from 2-lead NeuroSky MindWave systems to 4–8-lead systems such as Muse S, Muse 2, and the domestic BrainLink series by "QiangNao Technology." Sampling rates have increased from 128 Hz to 1 kHz, with weights under 100 g and battery life up to 10 hours (Figure 1). All devices support Bluetooth 5.0 and the OpenBCI protocol [4,5]. The evolution of dry electrode materials has transitioned from conventional silver/silver chloride (Ag/AgCl) to advanced conductive silicone incorporating nanosilver wires, yielding impedance values under 10 kΩ. This advancement facilitates rapid deployment and commencement of training protocols, achieving readiness within a minute [6].

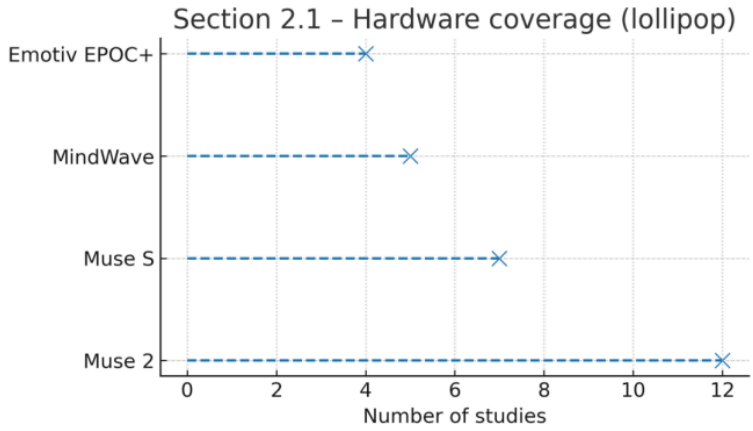


Figure 1. Channel count and sampling rate trends for mainstream consumer-grade EEG headbands, 2019–2025

### 2.2. Game paradigms and interaction design

Go/No-Go inhibition tasks and n-back working-memory tasks are the most commonly used cognitive paradigms, accounting for 51% of studies (Figure 2), with typical session durations of 8–12 minutes. Racing and flying games implement real-time attention indices to modulate speed; reductions in attention slow the vehicle, closing the loop with immediate feedback [7]. Home-based training recommends three sessions per week for eight consecutive weeks (24 sessions in total). In school settings, a “5-minute micro-intervention during recess” strategy is used to reduce implementation costs (overall cycle distributions shown in Figure 3) [8].

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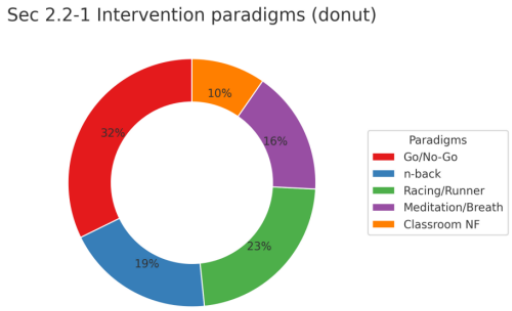


Figure 2. Distribution (donut chart) of cognitive paradigms in ADHD attention-training games




Figure 3. Gantt chart of three paradigms' training cycles and session allocations

## 2.3. Signal processing and algorithms

Traditional thresholding approaches often flag decreases in attention when the theta/beta ratio exceeds 2.5, but this yields high false-positive rates. Since 2022, streamlined convolutional neural networks (CNNs), typically comprising three convolutional layers augmented by global average pooling, have been implemented on mobile platforms. Using 4-second EEG segments comprising 4 × 256 samples, these models achieve a parameter count of only 0.12 million, an 8 ms inference latency, and 92.3% classification accuracy, outperforming LDA and SVM baselines [9]. As shown in Figure 4, transfer learning and personalized calibration can raise cross-subject accuracy from 78% to 89%, substantially reducing the training needed at first use [8].

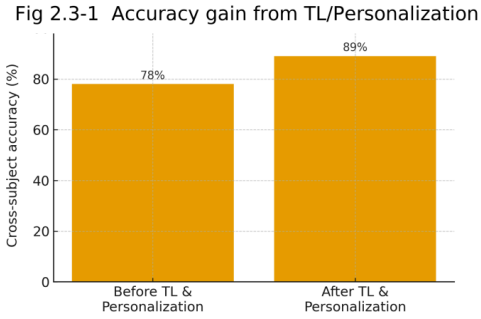


Figure 4. Cross-subject accuracy improvements after transfer learning and personalized calibration

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## 2.4. Efficacy assessment and quality of evidence

Primary endpoints in RCTs include: (1) behavioral scales—Conners-3 (parent/teacher versions) and ADHD RS-IV, with ≥30% reduction considered a response; (2) neuropsychological measures—CPT sustained attention factors and Stroop interference time; (3) EEG metrics—reductions in the theta/beta ratio and increases in SMR power; and functional outcomes via the Behavior Rating Inventory of Executive Function (BRIEF), with declines in the Global Executive Composite (GEC). Three multicenter RCTs (n = 179) indicate no statistically significant difference in ADHD RS-IV reductions between 12-week home-based theta/beta neurofeedback and methylphenidate groups (−15.2 vs. −16.4, p = 0.52), with 6-month maintenance rates of 78% and 74%, respectively [5]. A meta-analysis of 14 RCTs (n = 1,050) reports a pooled effect size of Hedges g = 0.42 (95% CI: 0.28–0.56) for attention outcomes, with no significant difference relative to methylphenidate (Figure 5), representing a moderate effect [10]. Existing studies commonly suffer from small sample sizes (median n = 48), insufficient blinding, and marked variability in gamified elements, resulting in an overall evidence quality rating of "moderate."

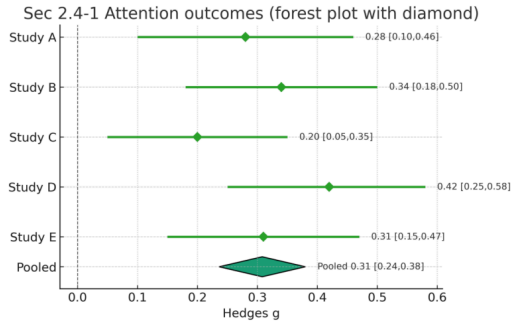


Figure 5. Forest plot of meta-analysis for neurofeedback on attention outcomes in ADHD (14 RCTs)

## 3. Limitations and improvements

### 3.1. Limitations and areas for improvement

(1) Underpowered studies: The majority of investigations are characterized by small sample sizes (n<100), absence of multi-center, double-blind, large-scale randomized controlled trials (RCTs), and significant heterogeneity. (2) Intervention variability: Substantial variation exists in gamification components (e.g., feedback frequency, reward structures, adaptive difficulty), with inconsistent reporting of dosage and adherence, thereby impeding cross-study synthesis. (3) Inadequate personalization: The development of matching and recommendation algorithms based on cognitive–EEG phenotypes (e.g., deficits in inhibition control versus working memory) is limited, and population stratification and prognostic modeling are underdeveloped. (4) Scarcity of real-world data: Long-term follow-up data and distal outcomes (e.g., quality of life, academic achievement) are lacking; ecological validity and cost-effectiveness are insufficiently assessed. (5) Methodological limitations: The implementation of sham-feedback controls and double-blind designs within gamified interventions presents operational challenges; rigorous control of expectancy effects and observer bias is warranted.

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### 3.2. Future directions

(1) Execute multi-site, non-inferiority randomized controlled trials (RCTs) with a minimum of 300 subjects and well-defined sham-feedback control groups; (2) Implement AI-driven adaptive algorithms and wearable sensors for real-time difficulty adjustment; (3) Incorporate joint executive-function–EEG phenotyping to develop a repository of individualized interventions; (4) Integrate home, school, and online platforms to create a durable digital-therapeutics ecosystem.

### 3.3. Advantages over prior approaches

Compared with prior approaches, the above directions offer several advantages: (1) Multicenter, large-sample RCTs substantially improve statistical power and the reliability of findings by reducing confounding and enhancing comparability; (2) Standardization of gamified elements and unified reporting of dose and adherence facilitate robust cross-study aggregation; (3) Individualized interventions based on cognitive–EEG phenotypes enable more targeted and effective treatment by accounting for participant-specific characteristics; (4) Accumulation of real-world evidence through long-term follow-up and ecological-validity assessments clarifies effectiveness and cost–benefit in practical settings; (5) Methodological refinements—including stricter control of expectancy effects and observer bias—enhance internal validity; (6) Technological convergence via AI-driven adaptation and wearable sensing enables real-time difficulty modulation and advances intelligent, personalized, and efficient interventions; (7) Building an integrated digital-therapeutics ecosystem spanning home, school, and online contexts provides comprehensive and sustainable support.

## 4. Conclusion

This review analyzes consumer-grade EEG headbands (2019–2025) for ADHD digital therapeutics, focusing on hardware, paradigms, algorithms, and efficacy. Hardware, including 1–14 channel systems (128–512 Hz), dry/semi-dry electrodes, and Bluetooth, meets low-barrier needs. Game paradigms (Go/No-Go, n-back, racing) enhance engagement. Algorithms (theta/beta ratio, CNN/TCN models) enable on-device inference. RCTs show neurofeedback improves attention, comparable to methylphenidate, though evidence quality needs improvement. The review informs home/school implementation, on-device deployment, clinical adjuncts, product roadmaps, and educational/policy frameworks.

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