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# Design and Implementation of a Gamified Attention Training App for Children with ADHD

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This study presents Focusa, a digital intervention aimed at enhancing attentional performance in children with Attention-Deficit/Hyperactivity Disorder (ADHD). The application combines gamified cognitive tasks, validated assessment tools, and customizable white noise playback to deliver an accessible, quantifiable, and non-pharmacological method for attention training. Focusa implements a structured training protocol incorporating the Reverse Stroop Test as both a pre- and post-intervention assessment. This design allows for objective measurement of attentional changes through two metrics: reaction time, which is defined as the average latency between stimulus presentation and a correct response, and error rate analysis. To strengthen visual tracking and short-term memory, which are both essential for sustained attention, the app includes a cup-and-ball memory task. In addition, The SNAP-IV questionnaire is embedded to assess ADHD-related behavioral symptoms and support early risk identification. An adjustable white noise feature is included to reduce environmental distractions and enhance user concentration. The system also integrates a data logging and analytics module that enables educators and caregivers to track individual performance over time, facilitating the creation of personalized intervention strategies and providing empirical evidence of training outcomes.

***Keywords:*** ADHD, gamification, cognitive training, white noise, SNAP-IV

## 1. INTRODUCTION

### 1.1 Clinical Characteristics and Intervention Challenges in ADHD

Children with Attention-Deficit/Hyperactivity Disorder (ADHD) frequently exhibit symptoms of inattention, impulsivity, and difficulties with goal-directed behavior. A substantial body of evidence indicates that behavioral and psychosocial interventions, such as behavioral parent training and classroom contingency management, produce reliable improvements in core ADHD symptoms and functional outcomes [30]. However, despite their demonstrated efficacy, access to these interventions remains limited in many regions due to disparities in healthcare resources, shortages of trained professionals, and the practical demands that such programs place on families. Pharmacological approaches may offer short-term symptom relief [29], but they are also associated with non-serious adverse effects such as sleep difficulties and decreased appetite [29]. To address these challenges, we developed Focusa, a digital intervention that combines gamified cognitive training,

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standardized assessments, and white noise support to enhance attentional control and functional outcomes in children with ADHD. The system employs a structured training protocol centered on the Reverse Stroop Test, administered both before and after the intervention to quantitatively evaluate attention through reaction time and error rate metrics. In addition, Focusa features a Cup-and-Ball memory game designed to strengthen visual tracking and short-term memory, which are both critical components of attentional development. The SNAP-IV questionnaire is integrated to facilitate early detection of ADHD-related behavioral symptoms. A white noise module is also included to minimize external distractions and help maintain a focused training environment. In contrast to many existing ADHD applications, Focusa incorporates validated assessment tools to track user progress and employs a reward-based system to sustain engagement. Its minimalist and child-friendly interface is carefully designed to reduce visual clutter and promote sustained attention throughout the training process.

### 1.2 Epidemiology of ADHD Worldwide and in Taiwan

According to the World Health Organization, ADHD affects approximately 3.1% of adolescents aged 10 to 14 and 2.4% of those aged 15 to 19 worldwide [31]. In Taiwan, national health statistics indicate that ADHD is among the most commonly identified neurodevelopmental conditions in school-aged children, with prevalence estimates generally reported in the 7–10% range. Government surveys have generally suggested that a notable proportion of school-aged children may meet diagnostic criteria for ADHD, reflecting its broad impact nationwide. Administrative health-care data in Taiwan similarly indicate that school-aged children represent a substantial share of newly identified ADHD cases in recent years. National epidemiological reports also indicate a high burden of ADHD symptoms among children evaluated for mental-health concerns. However, despite this high occurrence, the diagnosis and treatment of ADHD remain insufficient. Despite this prevalence, diagnosis and treatment rates remain disproportionately low, with only a minority of affected children receiving formal evaluation or sustained intervention. Healthcare-utilization reports similarly show that many children who meet diagnostic criteria do not receive ongoing clinical care. Reports from clinical settings suggest that only a portion of diagnosed children continue with long-term treatment, reflecting challenges in sustaining ongoing care. This persistent treatment gap underscores the importance of improving access, early identification, and caregiver support. Non-pharmacological interventions, including cognitive-behavioral and parent-training approaches, are increasingly emphasized as essential components of comprehensive ADHD management. In Taiwan, public-health agencies have introduced nationwide awareness initiatives and caregiver-support programs to address underdiagnosis and improve access to behavioral resources.

### 1.3 Gaps in Diagnosis, Treatment Access, and Clinical Follow-up

Healthcare institutions are essential to improving access to ADHD-related services. Many tertiary-care centers in Taiwan provide various psychosocial or behavioral training programs intended to support children's executive and social development. Clinical practitioners and professional groups have increasingly emphasized the use of behavioral strategies for caregivers, reflecting broader trends toward psychosocial approaches. Central

nervous system stimulants such as methylphenidate effectively reduce hyperactivity and enhance attention, but they may cause side effects including loss of appetite, insomnia, and headaches [29]. For younger children, behavioral approaches are generally preferred as an initial method of support, while medication is typically considered when symptoms cause significant impairment or when behavioral strategies alone are insufficient. However, access to non-pharmacological care remains limited in many regions, especially areas with shortages of trained professionals.

### 1.4 Limitations of Current Behavioral and Psychosocial Interventions

As noted above, behavioral therapies, executive-function training programs, and parent-management interventions are recognized components of ADHD care. However, their implementation in routine practice remains uneven, particularly in settings with limited clinical manpower and constrained service capacity.

In Taiwan, Various national overviews and survey findings have pointed to a gap between the high prevalence of ADHD and the comparatively lower rates of formal diagnosis and continuous treatment, indicating that many children do not receive regular behavioral support. In addition, clinic-based programs typically require repeated in-person visits and sustained caregiver involvement, which may be difficult to maintain for families facing geographic, economic, or time constraints. These limitations underscore the need for complementary interventions that can extend support beyond traditional clinical environments and provide more flexible, scalable options for sustaining attentional training in daily life.

### 1.5 Existing Non-Pharmacological and Digital Approaches

To address this gap, we developed a gamified digital intervention targeted at children and adolescents with ADHD. The application combines white noise-supported cognitive training, memory-based games, and standardized assessments, including the Reverse Stroop Test and SNAP-IV scale, to monitor attention changes and generate personalized plans. This approach offers a scalable, accessible, and data-informed complement to conventional care, especially for those lacking continuous clinical support.

### 1.6 Comparison with Existing ADHD Digital Interventions

A growing number of digital interventions have been developed to support children with ADHD. Among the most recognized is EndeavorRx, a U.S. FDA-approved therapeutic developed in the United States, which leverages action video game mechanics and adaptive stimulus-response tasks to improve attention. Another widely studied program, COGMED, a computer-based working memory training intervention, provides structured exercises designed to enhancing executive function. Although both interventions demonstrate some efficacy, their broader adoption is often limited by high implementation costs and platform constraints, including reliance on specific hardware or technology ecosystems [17]. To address these limitations, we developed Focusa, a low-cost, mobile-based, and self-guided digital intervention that integrates cognitive training with validated assessments, including the Reverse Stroop Test, along with environmental modulation via white noise. These features are seldom combined in existing ADHD interventions. Focusa also incorporates the SNAP-IV scale and enables remote monitoring of user progress, providing

a comprehensive and data-informed tool suitable for underserved populations. Notably, Focusa incorporates a child-friendly interface with gamified elements specifically designed for younger users. Its visual design adopts age-appropriate color schemes and reduces excessive tactile feedback to align with the attentional and sensory needs of children with ADHD.

To further clarify Focusa's positioning among existing ADHD interventions, we added a comparative analysis of mainstream attention training systems, including EndeavorRx and COGMED, as presented in Table 1. This table outlines key similarities and differences in aspects such as therapeutic framework, diagnostic integration, accessibility, adaptability to diverse clinical settings, and data transparency. Unlike EndeavorRx and COGMED, which require licensed devices or structured clinical sessions, Focusa emphasizes a low-threshold, self-administered approach suitable for home and community settings. Moreover, Focusa uniquely supports attention modulation in noisy environments and provides real-time, cloud-based progress tracking, offering a combination of features not commonly found in other systems. In addition, Focusa integrates a built-in attention stability analysis module that applies linear regression to quantify performance fluctuations over time and uses a sliding window approach to detect short-term instability and drift during training sessions. These analytical components not only facilitate transparent monitoring of cognitive engagement but also enable therapists and caregivers to obtain interpretable metrics for intervention planning. This combination of interpretability, adaptability, and accessibility underscores Focusa's innovation in supporting long-term attention training, particularly for underserved and resource-constrained environments.

**Table 1. Functional Comparison of ADHD Cognitive Training Tools**

| System / App | Prescription Required | Cost | Device Compatibility | Supervision Needed |
|---|---|---|---|---|
| Focusa | None | USD 5 per month | iOS / iPadOS | Not Required |
| EndeavorRx | Yes; physician prescription | USD 99 per 30-day prescription | iOS (publicly documented) | Yes |
| COGMED | No; requires certified coach | Provider-based pricing (typically USD 1,500–2,000 per program) | Browser-based (PC / tablet / phone) | Yes; coach supervised |

## 2. DESIGN RATIONALE AND THEORETICAL FOUNDATIONS

A study involving children with and without ADHD assessed the neurocognitive effects of white noise, focusing on its potential to enhance cognitive performance [1]. Participants aged 7 to 12 completed a visually cued Go/No-Go task under both silent and white noise conditions, during which behavioral responses and P300 EEG signals were recorded. The results showed that white noise significantly reduced omission errors in children with ADHD (from 14% to 10%), thereby aligning their performance more closely with that of typically developing peers.

### 2.1 Theoretical Models Underlying White Noise Effects

These findings suggest that white noise may serve as an effective non-pharmacological strategy for mitigating attentional deficits in ADHD. A subsequent study reported similar improvements in attention and task performance, although with modest effect sizes [11], thereby supporting both the Optimal Arousal Theory [3] and the Moderate Brain Arousal Model [15], which posit that white noise enhances cognition by moderately increasing cortical arousal [19]. Further evidence indicates that appropriate auditory stimulation, including white noise, can improve attention, task performance, and memory retention, particularly in children with attentional difficulties such as ADHD [16]. The expanding body of literature supporting the use of white noise as an adjunctive cognitive enhancer provides a strong theoretical basis for its inclusion in the present study [7].

Recent research highlights the effectiveness of memory-based digital interventions in enhancing attention and executive function in children with ADHD. These games strengthen short-term memory, attentional control, and cognitive organization while maintaining user motivation and supporting neurocognitive development. Incorporating immediate positive feedback during gameplay has been shown to improve stimulus-response accuracy and error correction [12], a process associated with dopaminergic activation that promotes motivation and sustained effort [18]. Gamified interventions have been linked to approximately a 15% improvement in executive function and a 20% reduction in attention-related errors, indicating gains in memory, reasoning, and task organization [17]. Through structured gameplay and progressive difficulty, such systems promote strategic learning, reduce inattentive behaviors, and support long-term academic and behavioral outcomes.

### 2.2 Memory-Based Training Integrated into Focusa

In this study, a Cup-and-Ball task was developed as the core training module for memory enhancement. In this game, users track a ball hidden under shuffled cups and identify its final location. The task engages visual memory, attentional focus, reaction speed, and logical reasoning, offering a dynamic and cognitively demanding experience. Complementary to this approach, Maniruzzaman et al. [10] applied machine learning techniques and functional near-infrared spectroscopy (fNIRS) to analyze brain activity during a Reverse Stroop task in children with ADHD [10]. Their results showed significantly longer reaction times (by 0.26 seconds) and higher error rates (0.32 additional errors) in ADHD participants compared to controls. Further studies suggest that children with ADHD perform better on the Reverse Stroop task than on the traditional version, as it reduces the need to inhibit automatic reading responses [20], making it a more sensitive indicator of attentional capacity [9][13].

### 2.3 Visual and Interface Design Considerations

Visual interface design also plays a key role in sustaining attention in children with ADHD. Research shows that specific color stimuli can enhance focus and reduce hyperactivity [21]. Moderate visual cues enable children with ADHD to perform at levels comparable to their neurotypical peers. Adaptive color interfaces are shown particularly effectiveness among children aged 10 to 12, significantly improving attentional engagement [14]. In Attentive User Interface (AUI) systems with gaze tracking, warm background tones paired with black text increased attention by 20 to 25%. High-contrast color pairs produced 18 to 24% gains, while blur-focused layouts emphasizing key content in red or

orange improved attention by 17 to 21%. Consistent with these findings, streamlined visual layouts with controlled contrast and minimal distractions can further stabilize sustained attention in children with ADHD. Based on these findings, the Focusa application applies low-saturation backgrounds in blue, green, and yellow, along with a high-contrast red target element to enhance visual salience, reduce cognitive load, and optimize attentional focus.

### 2.4 Cognitive Load, Motivation, and Difficulty Adaptation in ADHD

The design of Focusa incorporates an adaptive difficulty mechanism to prevent tasks from becoming either under-challenging or excessively demanding for children with ADHD. The theoretical basis for this approach is grounded in the Challenge Point Framework, which distinguishes between nominal difficulty, defined as the inherent demands of a task, and functional difficulty, defined as the level of challenge actually experienced by the learner [23]. According to this framework, learning is most effective when functional difficulty is maintained at a moderate level; tasks that are too simple provide limited informational value, whereas tasks that exceed processing capacity reduce engagement and performance. Recent studies applying this framework to ADHD populations support this principle. For example, Tollabi et al. demonstrated that children with ADHD achieve measurable learning gains when nominal task demands remain low but functional difficulty is adjusted to maintain a moderate challenge level [24]. Under such conditions, performance differences between ADHD and typically developing children were reduced, suggesting that task calibration plays a meaningful role in sustaining engagement.

Motivation is also known to modulate attentional performance in ADHD. Empirical evidence shows that increasing motivational value can improve vigilance, visual search, and divided attention, and can reduce performance gaps between ADHD and neurotypical peers [25]. These findings further support the need to dynamically regulate task difficulty, as maintaining tasks within an individually appropriate challenge range helps preserve motivation and attentional stability.

Based on these theoretical insights, Focusa employs a sliding-window, regression-based difficulty-adjustment mechanism that continuously updates challenge parameters according to recent reaction-time performance. Although the current pilot study did not manipulate difficulty as an independent experimental variable, the adaptive strategy implemented in Focusa aligns with well-established learning and motivational models for ADHD. Future research will focus on empirical validation of this mechanism's independent effectiveness, through controlled studies isolating the impact of adaptive difficulty on cognitive performance and user engagement.

### 2.5 Behavioral Assessment Using the SNAP-IV Rating Scale

The SNAP-IV Rating Scale is a widely used ADHD screening instrument based on two core symptom domains: inattention and hyperactivity/impulsivity. It has demonstrated strong psychometric properties, with reliability coefficients exceeding 0.91 and moderate to strong correlations with structured clinical interviews such as the Kiddie Schedule for Affective Disorders and Schizophrenia Present and Lifetime Version (K-SADS-PL) [4][8][22]. While parent-reported scores offer higher sensitivity in research settings, teacher-rated assessments more accurately reflect observable behavioral manifestations of

hyperactivity. Despite its limited specificity, the SNAP-IV remains a reliable and valid tool for both early detection and longitudinal monitoring. Although gender and socioeconomic status may influence ratings outcomes, age shows minimal impact, supporting its applicability across developmental stages [2]. In this study, the SNAP-IV is integrated into in the Focusa application to provide baseline behavioral screening and ongoing symptom monitoring. Combined with white noise-assisted training and memory-based gamification, these evidence- supported components form the foundation of Focusa's intervention model.

### 2.6 Professional Assessment Mechanism

The application integrates the Reverse Stroop Task as both a pre- and post-intervention assessment, administered through an interactive on-screen interface. To minimize stress in children with ADHD, the testing environment features a low-stimulation visual background with soft color hues, fostering a visually calming context that supports sustained attention [5][6]. Each session includes two assessments: a pre-test and a post-test, with each consisting of two 40-second rounds. Every round begins with a 10-second fixation phase, during which a central white dot appears to stabilize the user's gaze, followed by a 30-second task period. During the task, participants are instructed to tap the color corresponding to the semantic meaning of the displayed word.

### 2.7 Data-Driven Management

Focusa tracks the number of error and mean reaction time, alongside standardized assessments to quantify attentional performance. Reductions in these metrics indicate improved focus and provide evidence of the intervention's effectiveness. To improve interpretability, results are converted into percentage-based scores, allowing users to monitor progress across multiple sessions.

### 2.8 Versatile White Noise Functionality

Given the proven benefits of white noise in improving attention and task performance in individuals with ADHD, Focusa includes a flexible white noise module. Users can adjust the playback volume and select from multiple sound types. Customizable mixing options allow for the combination of sounds, such as ocean waves and rainfall, to create a personalized auditory environment.

### 2.9 User-Friendly Accessibility

By delivering the intervention through a mobile-based application, this study overcomes geographical and temporal limitations, ensuring convenient access at any time and from any location. This enables individuals with ADHD in remote areas to benefit from the intervention without reliance on traditional in-person services. Additionally, it reduces the burden on healthcare providers and minimizes both financial and time costs for users and their families.

### 2.10 Child-Centered Interface Design

The application features a visually stimulating and child-friendly interface designed to

enhancing user engagement. Cool-colored objects are presented against a warm-toned background to create clear visual contrast. A background blur effect is applied to emphasizes task-relevant elements and reduces cognitive load. Touch-prevention mechanisms are implemented to minimize accidental inputs and improve usability for young users.

### 2.11 Memory-Based Gameplay

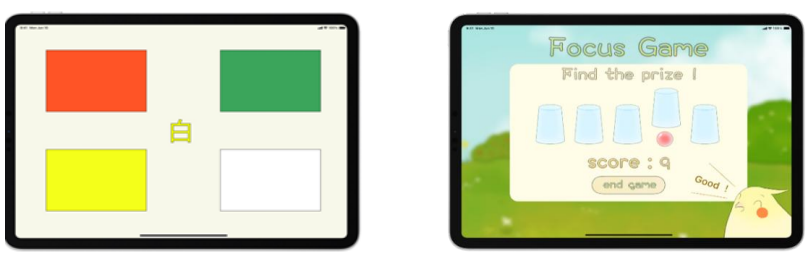
Given the difficulties that children with ADHD face in sustaining attention and processing memory, the core game in the application, Cup and Ball, employs a classic memory-based design. Users are required to track and recall the position of a target cup as it moves rapidly among distractors. This task supports the development of short-term memory, cognitive processing speed, and attentional control.

### 2.12 SNAP-IV Assessment Integration

Focusa incorporates the SNAP-IV Rating Scale, allowing users to complete self-reported screenings prior to the pre-test phase in order to evaluate their symptoms. The tool remains continuously accessible, supporting flexible use for ongoing ADHD screening and symptom monitoring.

## 3. SYSTEM DESIGN AND FUNCTIONAL COMPONENTS

The application integrates three primary components: a game module, the main interface, and pre- and post-evaluation functions, and is natively supported on both iPadOS and iOS. The study commenced with a systematic review of the literature to justify the need for attentional enhancement in individuals with ADHD, leading to the selection of the SNAP-IV Rating Scale as the primary assessment tool. Based on a comparative design analysis, the core game module was constructed, featuring a dynamic difficulty algorithm that adjusts both the number of cups and the velocity of the ball. An attention assessment module was also developed, incorporating validated cognitive paradigms, optimized testing intervals, and the SNAP-IV questionnaire. The interface was prototyped using Figma, with an emphasis on minimalist design and intuitive navigation to match the cognitive profiles of children with ADHD. To prevent accidental inputs, all button activations require a press duration of 0.5 seconds**.**




(a) (b)

Fig. 1. Schematic representation of the (a) pre-test interface; (b) main game phase featuring the “Cup-and-Ball” attention task.

As illustrated in Fig. 1(a), the application uses the Reverse Stroop Task for both a pre- and post-assessment, in which users are required to select the color that corresponds to the semantic meaning of the word displayed at the center of the screen. As shown in the top-right example, the correct response involves tapping the bottom-right white block. The system records both mean reaction time and error rate for each assessment. These metrics are then converted into percentage-based scores, offering users a standardized and interpretable reference for evaluating changes in attention before and after training. This dual-purpose assessment facilitates the measurement of attentional shifts and enhances user engagement by providing immediate feedback. Figure 1(b) displays the game interface, which features the core Cup-and-Ball task. At the start of each round, the ball's initial position is briefly shown. The cups then shuffle at a fixed speed for a number of repetitions that depends on the difficulty level. Once the shuffling concludes, the player must select the ball's final location. To boost engagement and sustain motivation, a scoring and feedback system is incorporated. Correct answers trigger randomly generated positive reinforcement messages, while incorrect responses prompt the message "Try again!", creating a supportive and interactive experience.

This adaptive feedback mechanism enhances both motivation and learning through immediate reinforcement and real-time correction. Cup animation is implemented using the with Animation modifier. The shuffleCups() function checks whether the remaining number of swaps (times) exceed zero. If not, shuffling stops and isShuffling is set to false. To maintain animation visibility, a 0.6-second delay is introduced using DispatchQueue.main.async after each swap. Two distinct indices are randomly selected to ensure that each shuffle is non-redundant. White noise playback is handled through the AVFoundation framework, offering customizable auditory environments. The AudioManager class, implemented as an ObservableObject, manages an AVAudioPlayer instance. Playback is initiated via playCurrentNoise(), while switchToNextNoise() cycles through tracks. Continuous playback is ensured by setting numberOfLoops = -1, which allows the audio to play without interruption. User test data is stored using CoreData integrated with CloudKit to support cross-device access. The persistentContainer initializes an NSPersistentCloudKitContainer using AppModel as the data schema. Upon launch, loadPersistentStores() loads the local dataset and synchronizes it with iCloud, maintaining data consistency and providing seamless access to user records.

Figure 2 illustrates the operational flow of the Focusa app. After launching the app, users are presented with the main screen, where they may optionally complete the SNAP-IV Rating Scale to assess ADHD-related symptoms. If selected, the app directs them to complete the associated self-report questionnaire. Users can also choose to configure background white noise by adjusting the volume and switching between different audio tracks, accessible through the "Adjust Volume and Variety" module. Once setup is complete, the user initiates the session by tapping the "Start Game" button. This begins with a Reverse Stroop pre-test, which measures baseline reaction time and error rate. The system then transitions to the Cup-and-Ball memory training game. After the game concludes, a post-test identical to the pre-test is administered. Finally, the user's performance results are displayed, and the app session ends.

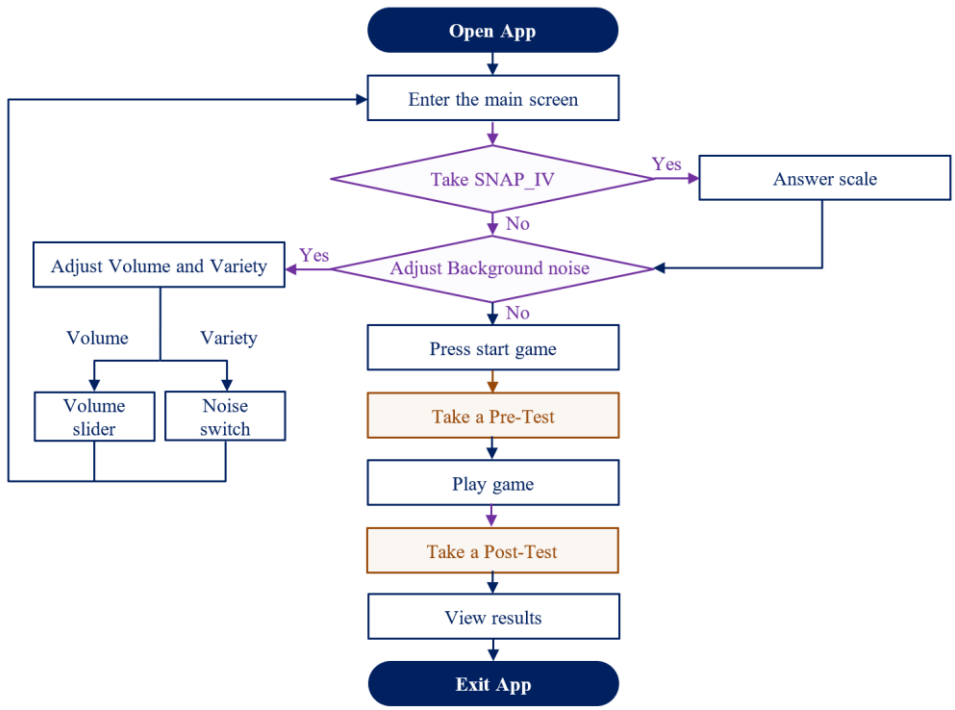



Fig. 2. Workflow of the attention training session in the Focusa app.

### 3.1 Animation and Transition Control Logic

The pseudocode in Algorithm 1 defines the visual logic for the interaction between cups and the hidden ball. Animation states are controlled by two Boolean variables, isSelected and liftCups, which define four distinct states: selected or unselected, and lifted or not lifted. These combinations form a finite-state model that governs predictable and consistent transitions. The scaleEffect function adjusts the cup's size between 1.0 and 1.03 when selected, creating a localized zoom-in effect triggered by a tap gesture. This transformation is applied immediately to enhance responsiveness and provide visual feedback. Concurrently, the offset parameter controls vertical displacement, moving the cup along the Y-axis from 0 to −25 when liftCups is true. This simulates the natural lifting motion of the cup to reveal hidden contents. Both scaleEffect and offset animations utilize an .easeInOut(duration: 0.5) easing curve to ensure smooth visual transitions and minimize perceptual disruption.

Intermediate animation states are computed in real time based on elapsed time, producing fluid and continuous motion that aligns with user interaction. When showBall is true, a ball image is rendered beneath the lifted cup using a fade-in transition. The fade-in effect is implemented via .transition(.opacity) combined with .easeInOut(duration: 0.3), producing a gradual opacity increase from 0 to 1. The visual effect supports intuitive user expectations and enhances perceptual coherence. All animations are implemented using declarative SwiftUI modifiers, ensuring synchronization with state changes and minimizing rendering conflicts. By leveraging declarative logic, the system automatically recalculates

view hierarchies, enhancing performance efficiency and ensuring visual consistency. From a design standpoint, the animation system operates within a reactive user interface framework.

**Algorithm 1** Operational Logic for Cup-and-Ball Rendering.

**Input:**
isSelected: Boolean flag indicating cup selection
liftCups: Boolean flag indicating whether the cup is lifted
showBall: Boolean flag indicating whether to reveal the ball
**Output:**
CupView: Animated rendering of the cup
BallView: Animated rendering of the ball (if revealed)

**Display:**
// Cup Image Rendering
Set CupWidth ← ScreenWidth × 0.118
Set Scale ← 1.03 if isSelected = true else 1.0
Set OffsetY ← −25 if liftCups = true else 0
Animate Scale and OffsetY using easeInOut(duration = 0.5)
// Conditional Ball Rendering
If showBall = true then
    Set BallWidth ← ScreenWidth × 0.05
    Set BallOffsetY ← −5
    Apply opacity transition with easeInOut(duration = 0.3)
End If
// Return Views
Return CupView, BallView if rendered

### 3.2 Real-Time Model Adaptation with Sliding Window Linear Regression

The pseudocode in Algorithm 2 defines the real-time adaptation mechanism implemented through sliding-window linear regression. The append(meanRT:difficulty:) function establishes an online learning framework that incrementally updates the regression model with each new data point. Each invocation appends the user's mean reaction time [meanRT] and the corresponding task difficulty [difficulty] to the arrays xs and ys. To ensure computational efficiency and temporal relevance, a fixed-length sliding window of size maxSamples (set to 50) is maintained. When this limit is exceeded, the oldest entries are removed using a first-in, first-out strategy, preserving only the most recent behavioral samples for model fitting.

Model parameters are recomputed in real time using the linearRegression(x:y:) function, which applies a closed-form solution to the least squares error minimization problem. This process minimizes the total squared loss function shown in Eq. (1).

$$L(m, b) = \sum_{i=1}^{n} (y_i - (mx_i + b))^2 \tag{1}$$

By taking the partial derivatives of $L(m, b)$ with respect to $m$ and $b$ and setting them equal to zero, the optimal coefficients for the linear regression model can be derived, as shown in Eq. (2):

$$m = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{n\sum {x_i}^2 - (\sum x_i)^2}, b = \frac{\sum y_i \sum {x_i}^2 - \sum x_i \sum x_i y_i}{n\sum {x_i}^2 - (\sum x_i)^2} \quad (2)$$

Here, $n$ represents the number of data points within the current window. The resulting slope $m$ and intercept $b$ are stored in the variable coeffs, which are immediately used by the predict(for:) function to estimate the appropriate task difficulty for a given reaction time input. This real-time model adaptation approach offers several advantages. The closed-form computation avoids iterative optimization procedures such as stochastic gradient descent, eliminating concerns regarding convergence rate, local minima, or hyperparameter sensitivity. The time complexity remains linear $O(n)$, but since $n \leq 50$ by design, the system achieves deterministic update latency, making it suitable for interactive applications. The use of a sliding window introduces temporal locality, emphasizing recent user behavior over older patterns. This design is particularly important for ADHD training scenarios, where performance may fluctuate significantly across short intervals due to fatigue, distraction, or momentary changes in motivation. By focusing on the most recent behavior, the model maintains a high degree of responsiveness, adjusting difficulty to sustain cognitive engagement within the user's current attentional threshold. Furthermore, the regression framework integrates seamlessly into the broader personalization architecture of Focusa. It complements the rule-based difficulty mapping mechanism described in Section 3.3 by generating a continuous-valued difficulty estimate, which is subsequently mapped to discrete game parameters. The predicted difficulty level directly influences key gameplay variables such as the number of cups, shuffle iterations, and animation speed, enabling nuanced, data-driven adaptation with minimal latency. The framework also supports modular expansion. For instance, future versions may incorporate additional features such as baseline attentional variability, time-of-day effects, or fatigue markers into the regression model to enhance predictive power. Similarly, incorporating regularization terms or confidence bounds could enable dynamic calibration of adaptation strength based on data stability.

**Algorithm 2** Sliding Window Linear Regression for Real-Time Prediction.

**Input:**
$x, y \in \mathbb{R}$ $(meanRT, difficulty)$
maxSample $\in \mathbb{N}$ $(sliding\ window\ length)$
**Output:**
Store $\beta = (m, b)$ //regression slope and intercept
**State:**
1: Arrays $X_s, Y_s \in \mathbb{R}$ $(data\ window)$
2: Coefficients $\beta = (m, b)$
**Step 1: Append new data point:**
3: $X_s \leftarrow X_s \cup \{x\}$
4: $Y_s \leftarrow Y_s \cup \{y\}$
**Step 2: Truncate if length exceeds maxSample:**
5: If $|X_s| >$ maxSample: Remove first element from $X_s$ and $Y_s$

**Step 3: Compute regression coefficients:**

Let $n = |X_s|$
Let $\sum x = \sum_{i=1}^{n} x_i , \sum y = \sum_{i=1}^{n} y_i$
Let $\sum xy = \sum_{i=1}^{n} x_i y_i , \sum x^2 = \sum_{i=1}^{n} {x_i}^2$
Compute denominator $D = n \sum x^2 - (\sum x)^2$
If $D = 0$:
    Set $m = 0, b = 0$
Else:
    Set $m = (n \sum xy - \sum x \sum y)/D$
    Set $b = (\sum y \sum x^2 - \sum x \sum xy)/D$
End If

### 3.3 Hybrid Difficulty Adjustment via Regression and Rule-Based Mapping

The algorithm presented in Algorithm 3 implements a hybrid mechanism for difficulty adjustment that combines regression-based estimation with a rule-based fallback. The input includes the user's average reaction time $x \in \mathbb{R}$ and current performance score $s \in \mathbb{Z}$.

**Algorithm 3** Adaptive Difficulty Adjustment Based on Reaction Time or Score.

**Input:**
score: Player's current performance score
latestMeanRT: Latest mean reaction time (optional)

**Output:**
cupCount: Number of cups to display
shuffleCount: Number of shuffles to perform
speed: Animation speed multiplier

**Update_Difficulty(score, latestMeanRT):**

If latestMeanRT is provided and valid:
    rt ← latestMeanRT
    pred ← model.predict(rt)
    (cup, shuffle, spd) ← mapDifficultyToSettings(pred)
    cupCount ← cup
    shuffleCount ← shuffle
    speed ← spd
Else:
    Find setting in difficultyTable where score ≥ minScore
    If found then:
        cupCount ← setting.cupCount
        shuffleCount ← setting.shuffleCount
        speed ← setting.speedMultiplier
    End If
End If
Return (cupCount, shuffleCount, speed)

When a valid reaction time is available, the system calculates a continuous-valued difficulty index $d$ using a first-order linear regression model, as defined in Eq. (3):

$$d = f(x) = mx + b \tag{3}$$

Equation (3) models the relationship between cognitive response latency and estimated task difficulty, where $m$ is the slope parameter indicating the sensitivity of difficulty to changes in reaction time, and $b$ is the intercept, which reflects the system's baseline difficulty offset. The choice of a linear formulation is motivated by two key factors: interpretability and computational simplicity. Once $d$ is computed, it is passed to a piecewise mapping function that transforms the continuous value into discrete gameplay parameters. As shown in Eq. (4), the mapping yields the number of cups $c$, the shuffle count $h$, and the animation speed multiplier $v$:

$$(c, h, v) = \begin{cases} (3,, 5, 1.00)\ if\ d < 1.5. \\ (4, 10, 1.07)\ if\ 1.5 \leq d < 2.5 \\ (5, 15, 1.15)\ if\ d \geq 2.5 \end{cases} \tag{4}$$

This mapping ensures that the user experience remains structured and interpretable, and responsive to subtle changes in performance. Discretization also facilitates downstream control over animation and interaction timing, which are critical for maintaining perceptual fluency in children with ADHD. If recent reaction time data are unavailable, such as during a cold start or sensor failure, the system switches to a rule-based mechanism. The most recent valid configuration is retrieved from a predefined difficulty table, based on the user's current score $s$, by selecting the entry with the highest minimum score threshold that does not exceed $s$, as defined in Eq. (5). This ensures robust system behavior under all conditions. All decision branches, whether regression-based or rule-based, execute in constant time $O(1)$, preserving interface responsiveness.

$$(c, h, v) = \max\{(c_i, h_i, v_i) \mid s \geq minScore_i\} \tag{5}$$

### 3.4 Online Data Ingestion and Adaptive Model Update

The pseudocode in Algorithm 4 defines a real-time learning mechanism that enables continuous model refinement through online regression updates. At the core of this mechanism is the append(meanRT, difficulty) function, which ingests incoming user data in the form of paired samples $(x, y) = (meanRT, difficulty)$. Each new observation reflects the user's average reaction time and the system-assigned task difficulty, and is appended to the respective arrays $x$s and $y$s. To maintain computational tractability and temporal relevance, the system employs a fixed-length sliding window with a maximum size $N_{\max}$ = 50. Once the number of samples exceeds this threshold, the earliest entries are discarded using a first-in, first-out strategy, formally expressed as Eq. (6).

$$x \leftarrow x_{2:n}, y \leftarrow y_{2:n} \tag{6}$$

**Algorithm 4** Sliding Window Update and Linear Regression Refit.

**Input:**
meanRT: Current mean reaction time
difficulty: Corresponding difficulty level
**Internal Variables:**
xs: Array storing recent reaction time inputs
ys: Array storing corresponding difficulty targets
maxSamples: Maximum number of samples allowed
coeffs: Regression coefficients to be updated

**Procedure Append(meanRT, difficulty):**
1: Append meanRT to xs
2: Append difficulty to ys
3: If length(xs) > maxSamples then
4: Remove first element from xs
5: Remove first element from ys
6: End If
7: coeffs ← linearRegression(xs, ys)
8: Return coeffs

This ensures that only the most recent interactions contribute to model fitting, emphasizing recency and minimizing the influence of outdated behaviors. The adaptive update mechanism preserves responsiveness to fluctuations in user performance, which is particularly relevant in ADHD-related scenarios where attentional stability may vary across short timescales. After the data buffer is updated, the system recalculates the linear regression parameters $(m, b)$ using the linearRegression(xs, ys) function. This function applies a closed-form solution to the least squares error minimization problem, as defined previously in Eq. (1) and Eq. (2), enabling efficient computation of the optimal regression coefficients without relying on iterative optimization. The updated parameters are stored in the global variable coeffs, which is immediately accessible to downstream modules such as the predict(for:) function in Section 3.2. The computational complexity of each update is linear with respect to $n(O(n))$, but since $n$ is upper-bounded by 50, the time cost is effectively constant in practice. This design supports real-time execution and ensures stable latency during gameplay.

### 3.5 Data Storage and Privacy Protection

Focusa employs a privacy-preserving, on-device data architecture to ensure that all user information remains secure and compliant with mobile software safety standards. The application does not transmit any identifiable data to external servers, third-party analytics services, or remote databases. All task-related metrics, including reaction time, accuracy, difficulty progression, and SNAP-IV responses, are processed and stored locally on the user's device. Focusa uses Apple's secure storage infrastructure. Performance data are stored through CoreData in a sandboxed environment, where all files automatically inherit device-level AES-256 encryption. Sensitive values such as session identifiers are stored in the iOS Keychain, which is protected by the Secure Enclave and accessible only after user authentication. No names, emails, IP addresses, advertising identifiers, or device identifiers

are collected. All records are associated with an internal, randomly generated session token to prevent reidentification. When users choose to enable multi-device synchronization, the app utilizes CloudKit's private database, which stores encrypted user records in Apple's cloud environment. CloudKit enforces end-to-end encryption and does not provide developers with access to the user's iCloud account or identity. As such, even synchronized data never leaves the Apple ecosystem and cannot be accessed by third parties. Users retain full control over their data. All stored information can be deleted by clearing the app's data or uninstalling the application. Focusa's design ensures that all collected data remain private, encrypted, and restricted to the user's device, with no external backend or developer-side data storage.

## 4. EVALUATION AND STATISTICAL ANALYSIS

This study presents the design and implementation of Focusa, a personalized digital intervention aimed at enhancing attentional control in children with ADHD. The system integrates behavioral data acquisition, real-time model adaptation, and cognitive training into a unified platform that operates independently of clinical supervision. By embedding a lightweight and responsive feedback loop, Focusa delivers context-aware difficulty adjustments based on the user's immediate performance. Unlike traditional interventions that rely on fixed task parameters or static session designs, Focusa employs an adaptive system architecture that continuously responds to moment-to-moment cognitive fluctuations. This design enables the system to maintain an optimal challenge level, sustaining user engagement while targeting executive attention and inhibitory control. The inclusion of standardized tasks and dynamic training modules ensures that both assessment and intervention components are grounded in evidence-based practice.

From a system engineering perspective, the application demonstrates computational efficiency through the use of closed-form regression updates and constant-time decision logic. The modular structure also allows for future integration with physiological sensors or third-party educational platforms without requiring major architectural revisions. By uniting algorithmic adaptivity with accessible mobile deployment, Focusa offers a new paradigm for scalable and data-driven ADHD support. The findings from this study provide foundational evidence supporting the viability of individualized digital interventions for attentional training. They also suggest promising directions for broader application in educational, clinical, and community-based contexts.

### 4.1 Experimental Procedure

A total of eight children were recruited for this study, including four typically developing participants (mean age: 9.75 years) and four children formally diagnosed with ADHD (mean age: 7.75 years). All participants followed a standardized assessment protocol. Children in the typically developing group completed a single session consisting of a 40-second pre-test, a 3-minute main game phase, and a 40-second post-test. In contrast, children in the ADHD group underwent two separate sessions with an identical structure. A one-minute rest period was provided between sessions to reduce fatigue-related effects. The ADHD group consisted of four male participants between the ages of 6 and 9. Specifically, the age distribution was as follows: one participant was 6 years old, two were 8 years old, and one was 9 years old, with a mean age of 7.75 years. All children in this

group had received a formal ADHD diagnosis from licensed child psychiatrists. One exception was a participant whose diagnosis was based on informal clinical observations provided by teachers and caregivers, in the absence of official documentation. Information regarding ADHD subtypes was not collected at the time of recruitment. At the time of testing, all participants in the ADHD group were undergoing pharmacological treatment with methylphenidate, commonly prescribed under the brand name Ritalin. According to caregiver reports, no participants presented with comorbid neurodevelopmental or psychiatric disorders, and none exhibited sensory or motor impairments that would interfere with digital task performance. This sample represents a relatively homogeneous cohort in terms of diagnostic classification, treatment status, and absence of comorbidity. Such uniformity supports the internal validity of the study, although it may constrain the generalizability of the findings to broader clinical populations.

To justify the session structure, two methodological considerations were incorporated into the study design. First, prior meta-analytic and review evidence indicates that children with ADHD exhibit higher intra-individual variability (IIV) and reaction-time variability (RTV) compared to typically developing peers, which can compromise the reliability of single-session assessments. Due to this increased variability, two separate sessions were administered to the ADHD group in order to obtain a more stable estimate of attention performance. In contrast, only one session was required for the typically developing group, whose performance tends to be more consistent.

In addition, this session design was chosen to reduce the impact of short-term fluctuations in attention often seen in ADHD. A comparison between the first pre-test and the second post-test across two sessions helps minimize moment-to-moment variability that can distort results within a single session. Repeated assessments are therefore more likely to reflect training-related changes accurately. This methodological choice is consistent with prior recommendations that emphasize repeated sampling to improve the stability of cognitive measurements in ADHD populations [26–28].

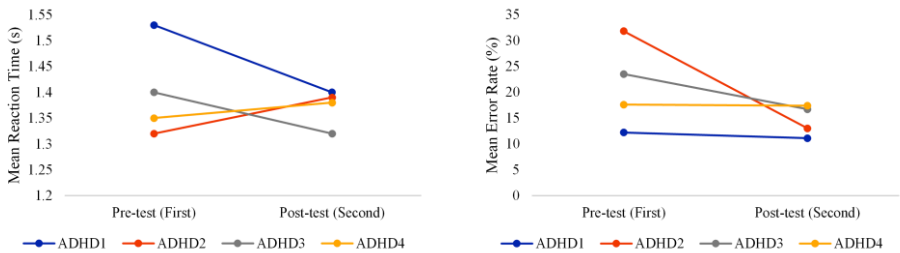
### 4.2 Behavioral Reference and Focusa System Tracking

The SNAP-IV rating scale was used during participant recruitment as a pre-screening tool to confirm that children in the ADHD group presented elevated symptoms of inattention, hyperactivity, or impulsivity. ADHD participants were rated by their caregivers using the SNAP-IV questionnaire prior to enrollment, providing a standardized behavioral reference that complemented the subsequent cognitive performance measures collected during the experiment. Within the Focusa system, the SNAP-IV is integrated as an optional behavioral module that can contextualize baseline attention profiles when available. It is designed to support, not replace, the platform's core tracking functionality. Focusa provides internal performance monitoring through automatic logging of reaction times, error rates, and adaptive difficulty progressions during task engagement. These behavioral data are securely stored using Apple's CloudKit infrastructure, ensuring data encryption and identity protection. This combination of structured behavioral referencing and real-time performance tracking enhances Focusa's potential for broader longitudinal applications.

#### 4.2.1 Behavioral Trends in Children with ADHD

Figure 3 summarizes the behavioral patterns observed in the ADHD group across two

experimental sessions. A comparison between the initial pre-test and the subsequent post-test assessments reveals an overall trend of enhanced attentional stability. Specifically, most participants exhibited faster response latencies during the post-test, reflecting improved cognitive processing speed. However, a few individuals demonstrated slight increases in reaction time in the second session, which may reflect intra-individual variability or increased task engagement and caution. Importantly, error rates declined consistently across all participants, indicating better inhibitory control and more accurate discrimination of visual stimuli.

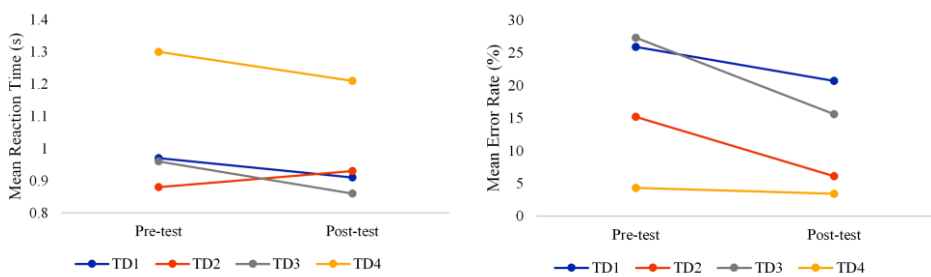



(a) (b)

Fig. 3. Comparison of attention metrics for children with ADHD: (a) Mean reaction time in the first session pre-test and second session post-test; (b) Mean error rate in the first session pre-test and second session post-test

### 4.2.2 Behavioral Trends in Typically Developing (TD) Children

The reaction-time and error-rate outcomes for the typically developing (TD) group, as illustrated in Figure 4, revealed relatively consistent performance across the two sessions. Overall, most participants demonstrated slightly improved reaction times in the post-test, suggesting modest gains in processing efficiency. This trend is reflected in the general downward pattern seen in Figure 4(a). However, TD2 showed a slight increase in reaction time during the second session, which may reflect natural intra-individual variability or increased cognitive caution during task execution. In terms of accuracy, error rates declined across all TD participants, as depicted in Figure 4(b), highlighting enhanced stimulus discrimination and task execution accuracy.




(a) (b)

Fig. 4. Comparison of attention metrics for typically developing (TD) participants: (a) Mean reaction time in the pre-test versus post-test; (b) Mean error rate in the pre-test versus post-test.

### 4.3 Results and Effect Size Analysis

Table 2 summarizes the performance metrics for the ADHD group across two sessions, capturing changes in error rate, correct mean reaction time (RT), and overall mean RT. A comparison between the first pre-test and the second post-test reveals a 6% reduction in error rate and a 0.09-second improvement in correct reaction time. The observed reductions in both error frequency and response latency suggest a meaningful improvement in attentional control and task engagement. Effect sizes calculated using Hedges' $g$ indicate moderate treatment effects, with values of 0.64 for error rate and 0.74 for correct mean RT. These findings support the effectiveness of the intervention in enhancing attentional performance and processing speed in children diagnosed with ADHD.

**Table 2. Performance Metrics for the ADHD Group Across Two Sessions.**

| Test Phase | | Mean Error Rate (%) | Mean RT for Correct Trials (s) | Overall Mean RT (s) |
|---|---|---|---|---|
| Pre-Test | First | 21.28 ± 8.40 | 1.40 ± 0.093 | 1.30 ± 0.096 |
| | Second | 14.55 ± 3.00 | 1.37 ± 0.036 | 1.32 ± 0.074 |
| Post-Test | First | 20.05 ± 5.67 | 1.39 ± 0.074 | 1.32 ± 0.135 |
| | Second | 15.35 ± 7.77 | 1.31 ± 0.116 | 1.27 ± 0.188 |

| Effect size | Mean Error Rate: Pre-Test 1 vs. Post-Test 2 | Mean RT for Correct Trials: Pre-Test 1 vs. Post-Test 2 |
|---|---|---|
| Hedge's $g$ | 0.64 | 0.74 |

SD: Standard Deviation

RT: Reaction Time

Table 3 displays the data for typically developing children. While their performance was generally more stable compared to the ADHD group, the results still indicate measurable improvements. Between the pre-test and post-test, the mean error rate decreased by 7%, and the mean RT for correct trials improved by 0.06 seconds. The effect size, calculated using Hedges' $g$, was 0.62 for error rate, indicating a moderate effect, and 0.35 for mean RT, which is considered small. These results demonstrate that even among children without a formal ADHD diagnosis, the training protocol implemented in Focusa may modest attentional benefits, particularly in reducing performance errors.

**Table 3. Performance Metrics for the Typically Developing Group.**

| Test Phase | Mean Error Rate (%) | Mean RT for Correct Trials (s) | Overall Mean RT (s) |
|---|---|---|---|
| Pre-Test | 18.18 ± 10.71 | 1.09 ± 0.166 | 1.03 ± 0.186 |
| Post-Test | 11.45 ± 8.09 | 1.03 ± 0.127 | 0.98 ± 0.158 |

| Effect size | Mean Error Rate: Pre-Test 1 vs. Post-Test 2 | Mean RT for Correct Trials: Pre-Test 1 vs. Post-Test 2 |
|---|---|---|
| Hedge's $g$ | 0.62 | 0.35 |

SD: Standard Deviation

RT: Reaction Time

Although the present study did not include long-term follow-up assessments, the short-term improvements observed across consecutive sessions provide a basis for cautious inference regarding potential maintenance effects. Prior research has shown that children with ADHD benefit from training protocols that deliver frequent, high-density task repetitions together with immediate performance feedback. Rosch and Hawk [12] demonstrated that rapid trial-based reinforcement improves stimulus processing and reduces attentional lapses in the short term, while Söderlund et al. [16] reported comparable short-term gains when external auditory stimulation is continuously applied. More recently, Tollabi et al. [24] found that repeated practice within a single session supports measurable learning gains in children with ADHD under optimal challenge conditions. Motivational studies further indicate that increased engagement can reduce attention deficits during repeated trials [25].

Taken together, these findings suggest that the short, high-frequency, feedback-driven training structure used in Focusa may support transient stabilization of attention, as reflected in the improvements observed within two closely spaced sessions. While no claim can be made regarding long-term maintenance effects, the mechanisms underlying Focusa, including white-noise modulation, adaptive difficulty, and dense trial repetition, are consistent with factors previously associated with short-term attentional enhancement in ADHD populations.

## 5. DISCUSSION AND IMPLICATIONS

### 5.1 Contributions and Practical Implications

The results of this pilot study indicate that brief, structured, and mobile-based cognitive training can produce measurable short-term improvements in attentional performance among children with ADHD. These findings speak directly to the broader clinical challenge that motivated the development of Focusa—namely, the difficulty many families face in accessing consistent behavioral support, formal cognitive assessments, and long-term follow-up. The reductions in error rate and reaction time observed across sessions suggest that Focusa's combination of adaptive task difficulty, white-noise modulation, and standardized cognitive measures may offer a feasible supplementary option for sustaining attentional practice outside traditional clinical environments. While exploratory in nature, the results highlight the potential role of accessible digital tools in addressing gaps in daily behavioral support for children who may not receive regular in-person intervention.

Focusa provides a practical adjunct for teachers, clinicians, and caregivers who seek non-pharmacological methods to support attentional training. Because the system operates entirely on mobile devices, it can be implemented in rural or low-resource settings where regular clinical services are limited. The automatic logging of reaction time, error rate, and task-difficulty adjustments generates objective measures that can complement behavioral observations and support preliminary identification of attention-related difficulties in both home and school contexts.

Academically, this study contributes by demonstrating a multimodal digital intervention model that integrates adaptive difficulty calibration, auditory modulation, and validated cognitive assessments within a single platform. The real-time adjustment mechanism

illustrates how performance data can be used to maintain moderate functional challenge, offering a foundation for future work on closed-loop cognitive training paradigms. The combination of white noise with visuocognitive tasks further provides a useful experimental environment for examining sensory–cognitive interactions and their relevance to ADHD intervention design.

Digital tools such as Focusa may help reduce the burden on clinical manpower by extending screening and supportive training beyond hospital settings. When paired with behavioral instruments such as the SNAP-IV and longitudinal performance records, such systems can assist schools, community centers, and public health programs in identifying attentional difficulties earlier and making timely referrals. This potential aligns with ongoing educational and public-health efforts to improve ADHD detection, treatment continuity, and access to early intervention.

### 5.2 Limitations and Future Work

Focusa provides a practical adjunct for teachers, clinicians, and caregivers who seek non-pharmacological methods to support attentional training. Because the system operates entirely on mobile devices, it can be implemented in rural or low-resource settings where regular clinical services are limited. The automatic logging of reaction time, error rate, and task-difficulty adjustments generates objective measures that can complement behavioral observations and support preliminary identification of attention-related difficulties in both home and school contexts. In response to the recognized need for broader empirical validation, we acknowledge that establishing the superiority and applicability of Focusa across diverse populations requires additional experimentation. Future research must adopt large-scale randomized controlled trial (RCT) designs, stratified by variables such as age range, ADHD subtype, and comorbid conditions, to confirm whether the observed short-term improvements can be replicated consistently and sustained over time. These steps are essential to determine the system's efficacy in various real-world settings and to isolate the specific mechanisms contributing to its effects. By clarifying these future directions, the present study highlights not only Focusa’s immediate utility in supporting attentional practices outside the clinic, but also its potential for broader integration into multi-tiered behavioral health frameworks.

## 6. CONCLUSIONS

This study presents the design and preliminary evaluation of Focusa, an adaptive, mobile-based intervention targeting attentional control in children diagnosed with ADHD. The system combines standardized neurocognitive assessment, real-time difficulty calibration, memory-based training, and environmental auditory modulation into a cohesive digital therapeutic framework. This integration represents an emerging paradigm in digital mental health, emphasizing multimodal and personalized interventions grounded in empirical theory and algorithmic responsiveness. Behavioral outcomes from this pilot study indicate measurable improvements in attentional performance among children with ADHD, as reflected by reduced error rates and improved reaction time metrics. While the scope of this pilot study limits broad generalization, the observed effects nonetheless highlight the promise of this approach. These findings align with prior research demonstrating the

potential of structured, feedback driven digital tools to enhance attentional regulation and cognitive control in pediatric neurodevelopmental populations.

The use of closed-form regression, rather than iterative optimization enhances computational tractability and model interpretability. By avoiding gradient-based learning, the system eliminates the need for hyperparameter tuning or convergence checks, thereby improving execution efficiency on mobile devices. This design choice supports the broader objective of delivering clinically relevant digital therapeutics that are accessible, scalable, and capable of operating reliably in non-specialized settings. The potential translational value of Focusa extends beyond its technical attributes. By decoupling therapeutic access from traditional clinical infrastructure, the system addresses a persistent barrier in ADHD care: the limited availability of trained personnel and consistent behavioral intervention. This issue is particularly salient in low-resource or geographically isolated settings, where digital tools may serve as the primary mode of care delivery. The system's ability to generate longitudinal behavioral profiles also holds promise for integration into educational monitoring, remote consultation, and multi-stakeholder communication in child mental health services.

Although short-term gains were observed, these findings should be interpreted as exploratory rather than conclusive. Further evaluations using broader participant groups and extended observation periods will be valuable for assessing the system's durability and wider applicability. Such work will help clarify the conditions under which Focusa may provide advantages relative to alternative training tools. Future work integrating broader measurement approaches may deepen understanding of how different elements of the intervention influence attentional outcomes.

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