Development and Evaluation of a Digital Therapeutics System for Enhancing Executive Function Ability in Children with Attention-Deficit/Hyperactivity Disorder

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Abstract

Attention Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder characterized by deficits in attention, memory, and impulse control. Traditional digital therapeutics often suffer from repetitive content that reduces user engagement. In this study, we propose a novel digital therapeutic system integrated with a Convolutional Neural Network (CNN) to screen the probability of a user having ADHD. We developed an interactive therapeutic game designed to engage participants while assessing cognitive functions, including memory, concentration, and impulse control. A seven-week evaluation compared a test group using the therapeutic game with a control group, and performance was analyzed using three evaluation metrics. Results indicated that the control group consistently scored higher than the test group; however, the findings are limited by the small sample size.

Additionally, we developed a binary classification network to screen individuals for ADHD by analyzing the play logs of the proposed DTx system. Future work will expand the number of participants to improve statistical reliability and generalizability. Additionally, refining game mechanics to sustain long-term engagement and incorporating multimodal data sources is expected to enhance the accuracy and robustness of the proposed CNN-based ADHD screening model.

Introduction

Attention Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder characterized by persistent patterns of inattention, hyperactivity, and impulsivity, affecting both children and adults (Dvorsky and Langberg 2016). Traditional treatment often involves pharmacological interventions, such as stimulant medications like methylphenidate and amphetamines (Mattingly and Rostain 2017). While these medications can be effective in managing symptoms, they are associated with numerous side effects, including sleep disturbances, decreased appetite, and addiction. Notably, most stimulant medications are classified as Schedule II controlled substances because of their high potential for abuse and dependence, raising concerns about their use. Misuse of these medications without a prescription or in higher doses may lead to addiction, overdose, and other serious health consequences. These adverse effects emphasize the need for alternative, safer solutions to mitigate those effects.

To address these drawbacks of traditional medications, researchers explored digital therapeutics (DTx) as non-pharmacological interventions for ADHD. Akili Interactive developed EndeavorRx (Choi et al., 2023), the first FDA-approved game-based digital therapeutic for ADHD treatment in children aged 8 to 12. This prescription-only video game offers improved attention function by targeting neural systems through adaptive gameplay. Clinical studies discovered that EndeavorRx can lead to significant improvements in attention, with a 36.6% improvement observed in at least one objective measure of attention among participants (Business Wire 2023).

Despite the improved results, existing digital therapeutics like EndeavorRx have certain limitations. Studies have pointed out issues in small sample sizes in results, high variability in outcome measures, and a lack of long-term safety data. Additionally, challenges like user engagement and accessibility can affect the overall efficacy of these interventions. These limitations underscore the need for more personalized and scalable digital solutions for managing ADHD.

To solve these problems, we propose a novel machine-learning-based system that leverages adaptive algorithms to personalize therapeutic interventions for individuals with ADHD. This system aims to enhance user engagement and treatment efficacy by dynamically adjusting the therapeutic content based on real-time user performance and their behavior data. By integrating machine learning techniques, the system can identify patterns of the users, allowing for a more effective intervention in their symptoms. This solution would provide the potential to overcome the limitations of existing digital

Related Work / Background Knowledge

Digital Therapeutics for ADHD

Digital therapeutics(DTx) refers to software-driven interventions used to prevent, manage, or treat disorders. In order to treat the patient's disorder, digital tools such as virtual reality or wearable devices may be utilized to complement the traditional methods of treatment such as medication or counseling. Digital therapeutics allow for patients' better management of their conditions (e.g. by the digital treatment informing the patient when and how much medication they should take) and even alternative solutions to some drugs (e.g., by using digital stimuli to alleviate the symptom).

Figure 1. Playscene of EndeavorRX, a digital therapy for ADHD (Choi et al., 2023)

One digital therapy that is used for treating ADHD is EndeavorRx, a game that is intended to enhance the user's multitasking and impulse control abilities. By making the players repeatedly perform multitasking and impulse control in-game, the game aims to strengthen the patient's neural pathways related to the tasks, leading to benefits in treating the behavioral symptoms. EndeavorRX can be a good complement to the traditional method of treatment, since it is easily approachable and entertaining for most patients. The method also offers long-term effects while having virtually no side effects, as opposed to medicational approaches that require chemicals to affect the whole body and show decreased effects once the patients stop taking the drugs.

In order for digital therapeutics to be effective, the patients need to be motivated and focused on the treatment. To achieve this, the game could alter its difficulty levels based on the patient's performance so that the patient does not feel overwhelmed or bored with the treatment and can engage in it for a long time. Additionally, the game, by comparing a user's performance with the data from others, could also serve a role as a pre-screening tool for ADHD.

Classification with Machine Learning

Classification is a supervised machine learning task in which input data, such as images, text, or signals, are assigned to one of several predefined categories or classes. For example, an image classifier may determine whether a picture contains a cat, dog, or bird. In this process, the model first takes input data, then extracts features, and finally outputs a class label or probabilities for each possible class. Convolutional Neural Networks (CNNs) are particularly effective for classification problems, especially when working with image data. CNNs are designed to capture spatial hierarchies within data by processing local regions through convolutional filters. These filters detect features such as edges, textures, and shapes, and deeper layers combine them to recognize more complex structures like objects or faces. A key advantage of CNNs is weight sharing, where the same filter is applied across different parts of the input, reducing the number of trainable parameters and making the model more efficient. CNNs also provide translation invariance, allowing features to be recognized regardless of where they appear in an image. Unlike traditional approaches that rely on hand-crafted features, CNNs learn relevant features directly from raw data, which makes them highly adaptable and powerful for classification tasks.

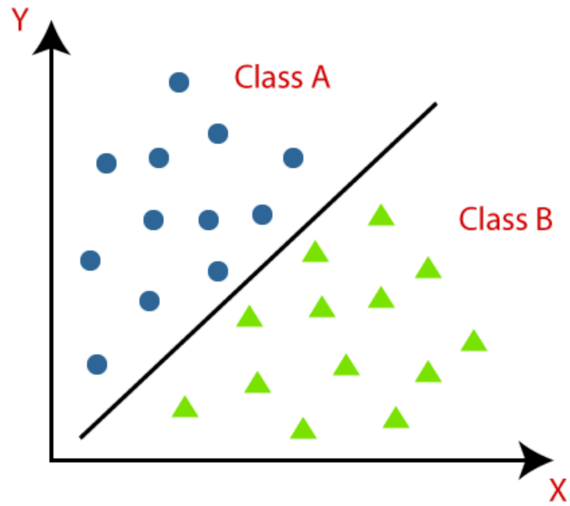

Figure 2. Binary classification (Dridinour 2024)

CNN-based classification has found applications across a wide range of fields. In medical imaging, CNNs are used for tumor detection in MRI and CT scans (Salehi et al., 2023), diabetic retinopathy screening, and cancer diagnosis through histopathology slides. In healthcare and neuroscience, they are applied to analyze EEG or MEG signals for conditions like ADHD, epilepsy, and sleep disorders, as well as in computational pathology for generating or interpreting virtual staining.

In this research, we developed an ADHD screening system using a CNN-based binary classifier, which takes the play log of a DTx system as input and outputs the probability of whether an individual has ADHD. The detailed information of the proposed system is explained in the following methodology section.

Methodology

Architecture of Proposed ADHD Digital Therapeutics

Our research proposes the architecture for a digital therapeutic intervention designed to address Attention Deficit Hyperactivity Disorder (ADHD) symptoms. The design emphasizes the key elements identified as crucial for effective engagement and therapeutic benefit, particularly focusing on enhancing cognitive ability impacted by ADHD.

A successful therapeutic game for ADHD involves several imperative features (Oh et al., 2024). First, the game should be designed to maintain a “flow state” in the user (Hutson and Hutson 2024). This concept refers to a state of optimal experience through complete immersion and focused attention on an activity while performing tasks. Achieving a flow state requires a careful balance between challenges and skills. If the game becomes easy, the subjects may possibly become bored and disengaged. Conversely, if the game is challenging, the users become frustrated and give up. Therefore, an engaging ADHD game requires adaptive difficulty scaling, personalized to individual users’ abilities and progress, ensuring a continuously engaging and challenging experience. This customization is essential for prolonged engagement and for reinforcing therapeutic effects.

Second, the game should be designed to enhance multitasking abilities actively. Individuals with ADHD often struggle with divided attention and managing multiple tasks simultaneously. The game’s design should incorporate tasks that require the player to switch between different cognitive demands, manage competing stimuli, and prioritize tasks effectively.

Third, the game must focus on strengthening inhibitory controls. Impulsivity is a core symptom of ADHD, which is often manifested as difficulty inhibiting responses and actions. Game mechanics requiring the player to pause, think, and act can directly target and strengthen the necessary cognitive functions. By creating situations where the subject should limit themselves and find satisfaction in the game, it can gradually improve and be transferred into real-life situations.

Fourth, the game should incorporate elements to enhance working memory. Working memory is the capacity to hold and manipulate information in the mind for ephemeral periods. So, it is frequently related to individuals with ADHD. Game tasks that require the player to remember instructions, track multiple pieces of information, or perform a sequence of steps can help exercise and strengthen cognitive capacity. This is achieved through progressively increasing the complexity of the game’s demands,

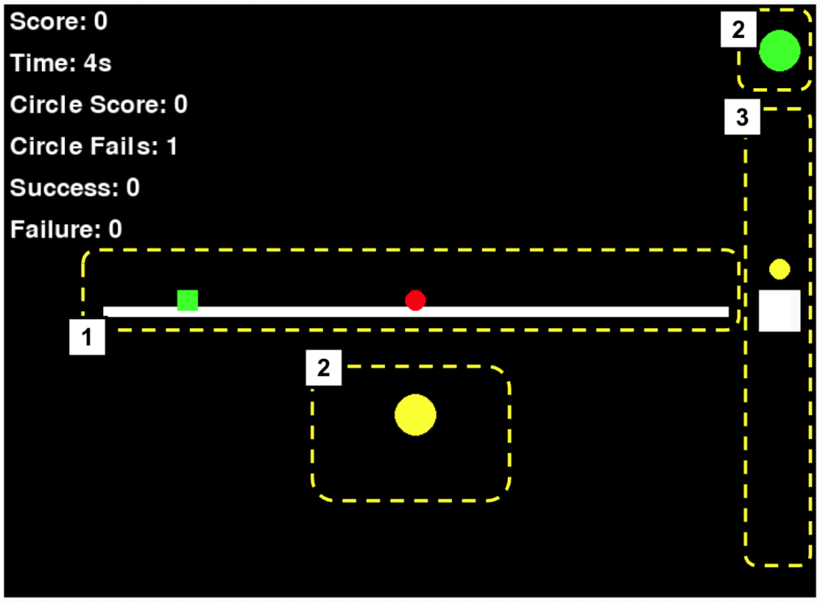

Figure 3. Architecture of the proposed network

Figure 3 shows a gameplay screen of the proposed digital therapeutic. The user is given a task to correctly manipulate the three balls shown on the screen by pressing the corresponding keys. The first task is intended to reinforce the working memory of the user. The first part of the task(see Figure 2, area labeled '1') is to adjust the angle of the bar so that it slides down and collides with the square on the bar. In the second part(see area labeled '2'), the user has to trigger the disappearance of the circle beneath the bar, which spawns in irregular time intervals by pressing the spacebar when it is the same color as the circle in the upper right corner of the screen. In the third part(see area labeled '3'), the user has to trigger the disappearance of the small circle that falls from above the square as the two shapes collide with each other.

ADHD Screening Network

To screen for ADHD based on the game results of the user, the network converts the results into a matrix and inputs it to a convolutional neural network, which outputs the probability of the user having

ADHD. While the user is engaging in the gameplay, the log of the score of the user is recorded as a 2 dimensional user log sequence. The y-axis of the user log sequence represents the time of the log, and the x-axis represents features in each of the timesteps. Individual features contain information about whether tasks in the game are completed in the timestep of the log. The log sequence is then input into a convolutional neural network(CNN). The CNN performs convolution operations on the matrix to output features. Consequently, the features are input through a fully connected layer (which we call 'Anomaly Detection Network') that outputs a number between 0 and 1. The 'abnormal group' here indicates a group that performs significantly poorer compared to other users in the dataset. Although performing poorly in the game cannot act as a direct marker of ADHD alone, it can determine if the performance of a user in tasks that require ADHD-related cognitive abilities is significantly poorer compared to others and can therefore act as a pre-screening tool. The output of the anomaly detection network represents the probability of the user being in the abnormal group. An output of 1 means that the user is highly likely to belong in the abnormal group.

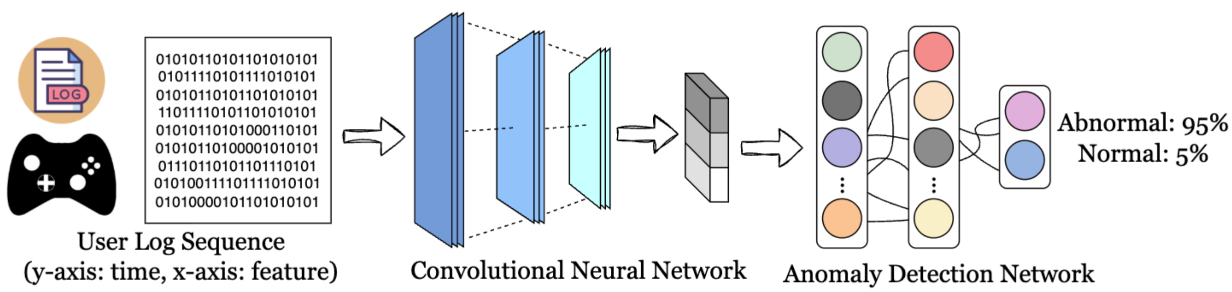

Figure 4. Architecture of the proposed anomaly detection network

$$L = -[\ y \times log_e(\hat{y}) + (1 - y) \times log_e(1 - \hat{y})\ ]$$

Equation 1: Binary cross-entropy loss function

To measure the loss of the anomaly detection network and optimize its parameters, a binary cross-entropy loss function is used. Here, y is the true label (0 for normal group, 1 for abnormal group) and ŷ is the prediction made by the anomaly detection network. The first part of the equation is canceled out when the true label is 0, and the result of the equation is the predicted probability that the patient does not belong to the abnormal group)

When the true label is 0, the first part of the equation is canceled out, and the equation yields the negative natural logarithm of the predicted probability that a given patient does not belong to the abnormal group. The same applies in reverse when the true label is 1.

Experimental Results

Experiment Protocol

To evaluate the ability of the system to enhance the cognitive skills of the user, the system was tested on real-life subjects. Data was collected from 14 anonymous participants aged from 10 to 16. Before using the proposed DTx, each participant was required to go through 3 tests that measured their cognitive skills. The testing tools respectively measured the memory, focus, and impulse control of the participant. The memory test involved a digital memory card game, in which participants were required to match hidden pairs of cards by recalling the position of the cards. The focus test was conducted by an online shell game, in which participants were required to identify the cup that has a ball in it among several cups that are shuffled. The impulse control test involved an online match game, where a figure that changes its color and shape is shown on the screen, and the participants were required to click the figure only when it is the same shape as the target figure, demanding inhibition of premature response and precise timing. Then, the participants engaged in the treatment for approximately 20 minutes a day for seven weeks. Each week, the participants' cognitive abilities were measured using the same tools stated above. The evaluation results of 3 participants from the test and control groups are given in Tables 1 to 4.

Performance Evaluation

Week	T1	T2	T3	C1	C2	C3
week-1	185	178	166	196	148	175
week-2	174	153	172	193	145	183
week-3	164	147	164	185	137	171
week-4	156	152	142	188	125	175
week-5	162	145	152	192	131	172
week-6	143	144	138	185	128	167
week-7	132	145	124	182	127	165

Table 1: Memory ability assessment

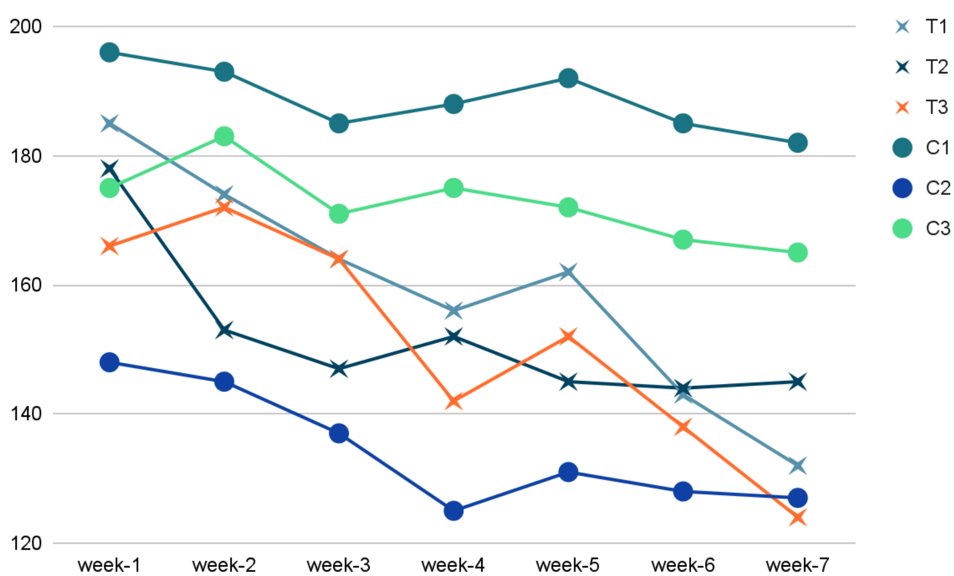

Figure 5. Memory ability assessment

Table 1 describes the memory ability assessment in weeks 1 to 7 for 3 of the subjects from each group. T1~T3 represent the 3 subjects from the test group, who were exposed to the proposed therapy. C1~C3 represent the 3 patients from the control group, who were not exposed to our therapy. The data in Table 1 is visualized by a line graph in Figure 5. The average time taken by the test group patients, shown in Table 1, decreased by 42.67 seconds, while the average time for the control group decreased by 15 seconds. This corresponds to an average reduction of 24.2% in the test group, compared to 8.67% in the control group. While both groups show enhanced abilities to perform the given task over time, the test group showed a greater difference over time, with the relative improvement of the test group being nearly three times greater. This implies that the test group's improved memory ability was not likely to be solely due to increased familiarity with the task over time but also a result of the intervention of the proposed therapy method.

Week	**T1**	**T2**	**T3**	**C1**	**C2**	**C3**
week-1	84	71	78	85	74	82
week-2	85	75	85	86	81	84
week-3	87	81	88	88	84	85
week-4	86	84	92	91	82	84
week-5	92	86	91	87	86	83
week-6	94	87	93	88	85	84
week-7	100	85	93	92	85	85

Table 2: Assessment of impulse control ability

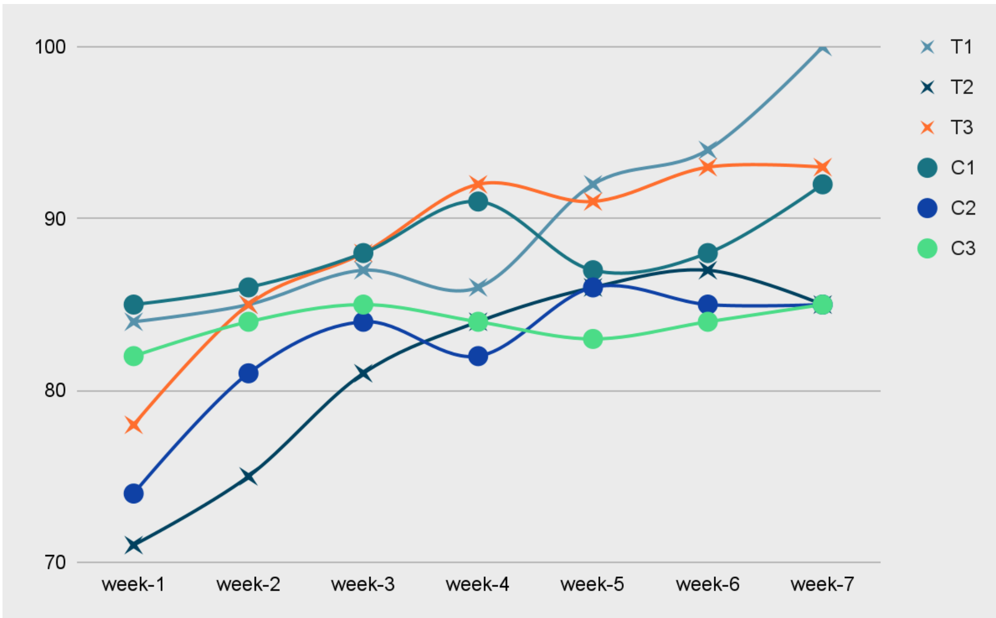

Figure 6. Assessment of impulse control ability

Table 2 shows the accuracy (in percentages) measured in the focus tests of 3 subjects in each of the groups. Figure 6 visualizes the data in Table 2 with a line graph. In the 3 subjects from the test group mentioned in the table, accuracy was raised by an average of 15%p, compared to 7%p in the control group. In the test group, the accuracy increased by 18%, compared to 8% in the control group. The results suggest that the intervention of the proposed method played a role in boosting the impulse control ability of the subject.

Week	T1	T2	T3	C1	C2	C3
week-1	54	62	57	52	58	49

week-2	60	62	71	53	55	55
week-3	72	65	73	55	57	57
week-4	74	67	75	54	61	54
week-5	71	69	74	57	63	55
week-6	72	71	76	61	67	56
week-7	73	74	76	62	68	59

Table 3: Assessment of concentration ability

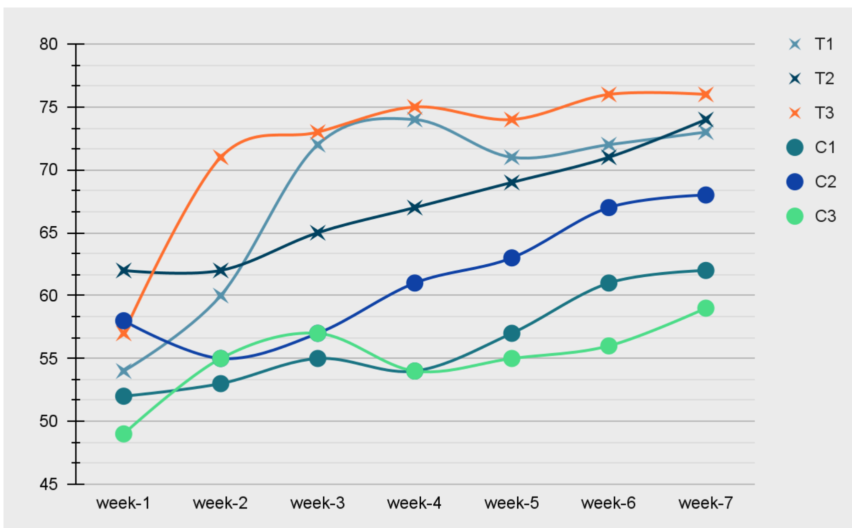

Figure 7. Assessment of concentration ability

Table 3 shows the accuracy (in percentages) in the concentration ability assessments performed on the patients. Figure 7 is a line graph that visualizes the data in Table 3. In the test group, the average increase in accuracy is 14%p, reaching 128% of the baseline. By comparison, the average increase in the control group was 10%p, reaching 119% of the baseline value. In the concentration ability assessment, it can be noted that the average accuracy of the test and the control group across the majority of operations was lower than that of the impulse control assessment, and that the average improvement of the performance is also greater in the concentration ability assessment. This can be due to the difference in the difficulty levels of the two tasks, meaning that the game was difficult to achieve a high accuracy level in first try but relatively easier with increased familiarity with the task, compared to the impulse control assessment, While habituation to the task may have played a role in the improved performance in the subjects, the difference between the improvements in test and control group proves the efficacy of the proposed therapy method in aiding the subject's concentration ability.

Conclusion

In our research, we proposed using a digital therapeutic with a Convolutional Neural Network to screen the probability of a user having ADHD. Our contributions included developing an interactive therapeutic game to address the fundamentals of ADHD. Previously, the digital therapeutic medications induced boredom due to their repetitive nature. So, through preliminary testing of memory, concentration, and impulse control, we compared the test group with the control group. Through a seven-week-long performance evaluation, we evaluated the performance using Binary Cross-Entropy Loss to detect the anomalies in the outputs. We observed that the control group scored higher than the test group in the results of our seven-week session. Despite the credible results, we intend to expand the number of experimental cases to increase the statistical analysis and verification of the significance of the difference between the two groups. A larger sample size will allow for more robust analyses, reduce the potential influence of outliers, and improve the generalizability of the results. The therapeutic game mechanics will be pursued to sustain participant engagement over prolonged usage. Incorporating multimodal data sources will also enhance the accuracy and reliability of the proposed ADHD screening model.

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