Neuroassist: Advance ADHD Supporting System

A.H.S Anjana, E.M.A Ekanayake, K.A.R Sanjula, G.M.J.K Gunathilake, Dr. Sanvitha Kasthuriarachchi

Faculty Of Computing Sri Lanka Institute of Information Technology Malabe, Sri Lanka

DOI: https://dx.doi.org/10.47772/IJRISS.2025.90600067

Received: 23 May 2025; Accepted: 27 May 2025; Published: 30 June 2025

ABSTRACT

ADHD (attention deficit hyperactivity disorder) is a neurodevelopmental condition that impacts children globally, leading to challenges with inattention, hyperactivity, and impulsiveness. This research proposes an AI-powered cognitive training system that utilizes machine learning (ML) and Continuous Performance Tests (CPT) to bridge the cognitive skill gap between ADHD and non-ADHD peers. A computerized Go/No-Go task is administered to non-ADHD children to establish baseline performance metrics. The same task is given to ADHD children, and the collected data is used to train a Random Forest model to identify cognitive deficits based on baseline comparisons. Based on these classifications, the system recommends tailored cognitive training activities, integrating gamification to enhance engagement and learning outcomes. The proposed approach ensures data-driven intervention strategies, addressing the limitations of conventional ADHD management. By continuously adapting to children's progress, the system bridges the cognitive skill gap between ADHD and non-ADHD peers, fostering improved attention and impulse control. This research highlights the potential of AI-driven personalized interventions in transforming ADHD management, offering a scalable and effective solution for cognitive skill development.

Keywords: ADHD, cognitive training, ML, CPT, attentional control, impulsiveness

INTRODUCTION

Attention Deficit Hyperactivity Disorder (ADHD) is a prevalent neurodevelopmental disorder affecting around 5% of children globally [1]. It manifests through symptoms of inattention, hyperactivity, and impulsivity, which can significantly impact a child's academic performance and social interactions [2]. Traditional interventions include behavioral therapies and pharmacological treatments, which might not fully address individual cognitive needs or provide personalized support.

The advent of digital technologies, particularly in the realm of Artificial Intelligence (AI) and Machine Learning (ML), presents new avenues for enhancing ADHD management. These technologies offer the potential to develop personalized learning and intervention tools that adapt to the unique cognitive profiles of individuals with ADHD [3]. Continuous Performance Tests (CPT) have been instrumental in assessing attentional capacities in ADHD; however, integrating these assessments with AI could revolutionize how interventions are tailored and delivered [4].

Cognitive skill development is crucial in mitigating the effects of ADHD, particularly in early and middle childhood. Researches have shown that cognitive training can enhance executive functions such as attention control, and cognitive flexibility, which are often impaired in children with ADHD. Engaging children in structured cognitive tasks helps reinforce neural pathways responsible for self-regulation and decision-making, promoting long-term improvements in focus, impulse control, and learning efficiency. Without proper cognitive interventions, children with ADHD may struggle to develop these fundamental skills, leading to persistent academic challenges and difficulties in social interactions.

School-age represents a critical developmental period where cognitive training can have a profound impact on planning, decision-making, and attentional control. During this stage, children's cognitive abilities are still highly plastic, making it an optimal time for targeted interventions that can shape their long-term cognitive

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VI June 2025

development. If left unaddressed, deficits in these areas can extend into adolescence and adulthood, affecting academic achievement and overall well-being. Therefore, focusing on this age group allows for early correction of cognitive deficiencies, fostering greater independence and adaptability in children with ADHD.

This research proposes the development of an innovative AI-powered tool designed for school age children to bridge the cognitive skill gap between ADHD and non-ADHD children. By leveraging machine learning algorithms, the tool will analyze performance data from CPTs to identify specific cognitive deficits in ADHD children. Based on these insights, personalized cognitive training activities will be recommended, focusing on enhancing attention and reducing impulsivity. The goal is to provide a dynamic cognitive training environment that adapts to the fluctuating needs of children with ADHD, thereby improving their cognitive functions and daily life interactions.

LITERATURE REVIEW

Traditional approaches to managing ADHD often include behavioral assessments and pharmacological treatments, which may not adequately address individual differences in symptom presentation and severity. In addressing the challenges associated with ADHD, recent advancements in technology have shown promising potential in creating personalized therapeutic and educational interventions.

Overview of Relevant Literature

A systematic review by Carolina Robledo-Castro et al. [5] evaluates the effectiveness of computer-based cognitive training, noting variable impacts on executive functions among children with ADHD, suggesting that the efficacy of such programs may depend heavily on their design and the specific cognitive functions they target.

Cognitive training systems are increasingly utilized to enhance cognitive functions and manage symptoms in various cognitive disorders, including Attention Deficit/Hyperactivity Disorder (ADHD). Common cognitive training systems, such as Cogmed and Lumosity, offer a range of brain-training games and tasks designed to improve cognitive functions like memory, attention, and problem-solving across diverse populations [6].

However, often lack specificity in addressing the unique needs of ADHD individuals, providing generic training that may not target the specific deficits associated with ADHD. specific training systems have been developed to address these limitations. For example, systems like Play Attention that tailor cognitive exercises to enhance attention and reduce impulsivity in ADHD patients [7].

A study by Natalia Wrońska and colleagues explores an iPad-based tool designed to improve only reading skills in children with ADHD by utilizing serious games for health [8]. This tool aims to enhance reading comprehension through engaging and interactive exercises, demonstrating significant improvements in attention and comprehension among participants. This approach illustrates the potential of digital tools to cater specifically to the cognitive needs of children with ADHD, enhancing traditional educational methods [8].

In a novel approach to digital therapeutics for pediatric ADHD, the STARS-ADHD randomized controlled trial, outlined by Scott H. Kollins et al. [9], explored the efficacy of AKL-T01, a video game-like intervention designed to improve attentional performance in children with ADHD. In this study also still exist limitations in personalization in cognitive training based on individual lacking skill area.

The research conducted by Achintha Thennakoon et al. [10] presents an "Individualized Edutainment and Parent Supportive Tool" designed to assist children with ADHD in managing and engaging in educational activities tailored to their attention levels. This mobile application integrates various modules to help parents interact effectively with their children and manage learning disabilities using predictive models. The study primarily relies on predefined behavioral patterns and data gathered from traditional settings, which may not fully capture the dynamic and spontaneous behaviors typical of ADHD children in varied environments.

The research by Pornsiri Chatpreecha and Sasiporn Usanavasin proposes a collaborative knowledge framework designed to support the personalized treatment of ADHD. It integrates a machine learning (ML) component that utilizes algorithms like Decision Trees classify ADHD from data gathered via a collaborative framework [11]. A significant limitation of this research is its reliance on conventional data collection methods, which might not fully capture the dynamic and context-dependent nature of ADHD symptoms. In this study in the data collection and assessment they have only involved parents and teachers to gather data due to COVID'19.

A study conducted by Balage Diniru Sandipa et al. proposes an innovative AI and ML-based intervention system tailored to enhance motivation and provide assistance to primary school children with ADHD. This system aims to personalize the intervention by adapting its content to the unique needs of each child, evaluated through standardized ADHD assessments.[12].

Recent advances in technology and cognitive neuroscience have led to the development of computer-based cognitive assessments and interventions that offer new avenues for personalized treatment strategies. Continuous Performance Tests (CPT) are particularly noteworthy, as they are effective in differentiating between ADHD symptoms based on error patterns and reaction times [13].

Context for the Study

The existing literature confirms that, in the realm of ADHD management, Continuous Performance Tests (CPT) are predominantly utilized as diagnostic tools to differentiate between ADHD and non-ADHD individuals by measuring their attentional capacities [14]. Also, recent advancements in machine learning (ML) have demonstrated significant potential in enhancing ADHD classification by enabling more robust, data-driven decision-making.

Knowledge Gaps

Considering the above existing studies, they demonstrate significant efforts towards integrating AI and ML in managing ADHD, yet they exhibit limitations in their assessment methods which may impact the personalization effectiveness of their interventions. The above frameworks rely primarily on data from parents and teachers, which may not capture the full spectrum of ADHD symptoms due to its static and indirect nature of observation. While innovative, utilizes standardized ADHD assessments that do not account for the real-time, dynamic behavioral changes of children during interactions.

While CPTs are effective in identifying attentional deficiencies characteristic of ADHD, their application has largely been limited to classification purposes and not extensively integrated into personalized intervention strategies using machine learning (ML). This represents a significant limitation in the practical utility of CPT, as the potential for ML to analyze CPT data to tailor interventions based on real-time performance remains largely untapped. Every ADHD child is unique, and they react differently. It is valuable to accurately identify their weaknesses and performance levels, especially when aiming for effective personalization.

In addition, there is a notable lack of systems that compare ADHD performance directly against baselined non-ADHD performance to effectively measure and bridge the cognitive skill gap. This comparative approach is crucial for accurately assessing the effectiveness of interventions and ensuring that they are truly aligned with the developmental benchmarks of non-ADHD peers. Therefore, the research problem centers on developing a system that not only utilizes CPT for initial ADHD identification but also leverages this assessment tool to offer real-time, personalized cognitive activity recommendations based on direct comparison with non-ADHD performance data.

Research Objectives

The development of this system involves several critical steps: (1) establishing baseline cognitive performance metrics from non-ADHD children to serve as a comparison, (2) analyzing CPT data from ADHD patients to identify specific deficits, and (3) training a machine learning model to intelligently recommend personalized activities based on these insights.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VI June 2025

METHODOLOGY

This section primarily concentrates on the methodology, which includes Initial CPT test Development, Baseline Performance Metrics on CPT, Data Collection and Analysis on ADHD Sample, ML integration and Development of Cognitive Improvement Activities.

Initial CPT test Development

In this research, it employs the Go/No-Go task as a Continuous Performance Test (CPT) to assess attention and hyperactivity metrics in both ADHD and non-ADHD children. Also, this task serves as an initial identification tool to pinpoint attention and hyperactivity issues before recommending tailored cognitive activities.

As shown in Figure 1 the Go/No-Go task requires participants to respond to specific stimuli ("Go" signals) and withhold responses to others ("No-Go" signals), effectively measuring response inhibition and sustained attention. Studies have demonstrated that performance on the Go/No-Go task correlates with caregiver and teacher reports of inattention and hyperactivity–impulsivity in children, highlighting its utility in distinguishing between ADHD and non-ADHD populations [15].

Figure 1: Go/NoGo Task

By integrating the Go/No-Go task into the assessment protocol, the research aims to obtain objective metrics of attentional control and impulsivity. These metrics will inform the development of personalized cognitive training interventions designed to address the specific deficits identified during the initial assessment.

The task helps to identify ADHD deficits by analyzing response accuracy and reaction time.

- Inattention: Detected through errors of omission where the participant fails to respond to targets.
- Impulsivity: Identified through errors of commission where the participant incorrectly responds to non-targets.

Baseline Performance Metrics on CPT

To establish baseline performance metrics, a computerized Go/No-Go task is administered to a control group of non-ADHD children aged 10-12 years. This task lasting specific time period, was designed to measure key cognitive parameters, including sustained attention, impulsivity, and reaction time variability.

Participants were screened to confirm the absence of ADHD symptoms using standardized behavioral checklists during the data collection. The control group is carefully selected to ensure that all participants are within the same educational level, minimizing variability due to differences in cognitive development and learning exposure. Each child performed the computerized Go/No-Go task in a controlled environment with minimal distractions for the same time period. Stimuli were presented at fixed intervals, requiring participants to respond to "Go" signals while withholding responses to "No-Go" signals.

For baseline data collection, the following key metrics are recorded:

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VI June 2025

- Age and Gender – to account for demographic variations.
- Errors of Omission – instances where the participant fails to respond to a Go stimulus, indicating inattention.
- Errors of Commission – incorrect responses to No-Go stimuli, reflecting impulsivity.
- Reaction Time (RT) – the time taken to respond to Go stimuli, indicating processing speed and attentional efficiency.

The collected performance data are then statistically analyzed to establish normative benchmarks for this age group. Specifically, as per the Figure 4, average reaction times and error rates are computed for each gender to define standard performance metrics. This baseline data serves as a reference point for comparison when evaluating the performance of children with ADHD, helping to identify significant deviations that may indicate cognitive deficits in attention and impulse control.

Table 1: Calculated Baseline Performance Metrics

	Female	Male
Average Omission Errors	$0.945 \approx 1$	$1.04 \approx 1$
Average Omission Errors	$1.615 \approx 2$	$1.94 \approx 2$
Average Reaction Time	475.98	460.35
Total Non- ADHD data	318	

Data Collection and Analysis on ADHD Sample

To evaluate cognitive performance in children with ADHD, the Go/No-Go task is administered under the same conditions as for the non-ADHD control group. The ADHD dataset used in this study consisted of 963 records, providing a substantial basis for analysis and model training. The collected data focuses on the same key cognitive metrics to assess attentional control and impulsivity levels as collected from the non-ADHD control group.

Each record from the ADHD sample and healthy sample is labeled based on deviations from the baseline performance metrics established using the non-ADHD control group. The baseline establishment process involves statistically analyzing the non-ADHD group's average reaction time, omission errors, and commission errors to create a normative reference range. A threshold is then determined based on standard deviations (±1 SD) from the mean, enabling the differentiation between typical and atypical cognitive performance.

The deviation-based labeling process categorizes participants based on their performance deviations from the established baseline.

- Low Attention: Participants with significantly higher omission errors or slower reaction times compared to the baseline.
- High Impulsivity: Participants with higher-than-baseline commission errors, indicating difficulty inhibiting responses.
- Combined Deficits: Participants exhibiting both high omission errors and high commission errors, signifying severe attention and impulsivity challenges.
- None: Participants performing within the normative range for both attention and impulsivity metrics.

ML integration

The collected and labeled data on cognitive performance in children with ADHD and non-ADHD were utilized to train machine learning models. A Random Forest classifier was employed to predict performance levels based on key cognitive metrics, including reaction time, omission errors, and commission errors. This approach leveraged the model's ability to handle complex patterns and variations in cognitive performance, ensuring reliable classification of attention and impulsive levels among the participants.

A. Development of Cognitive Improvement Activities and system workflow

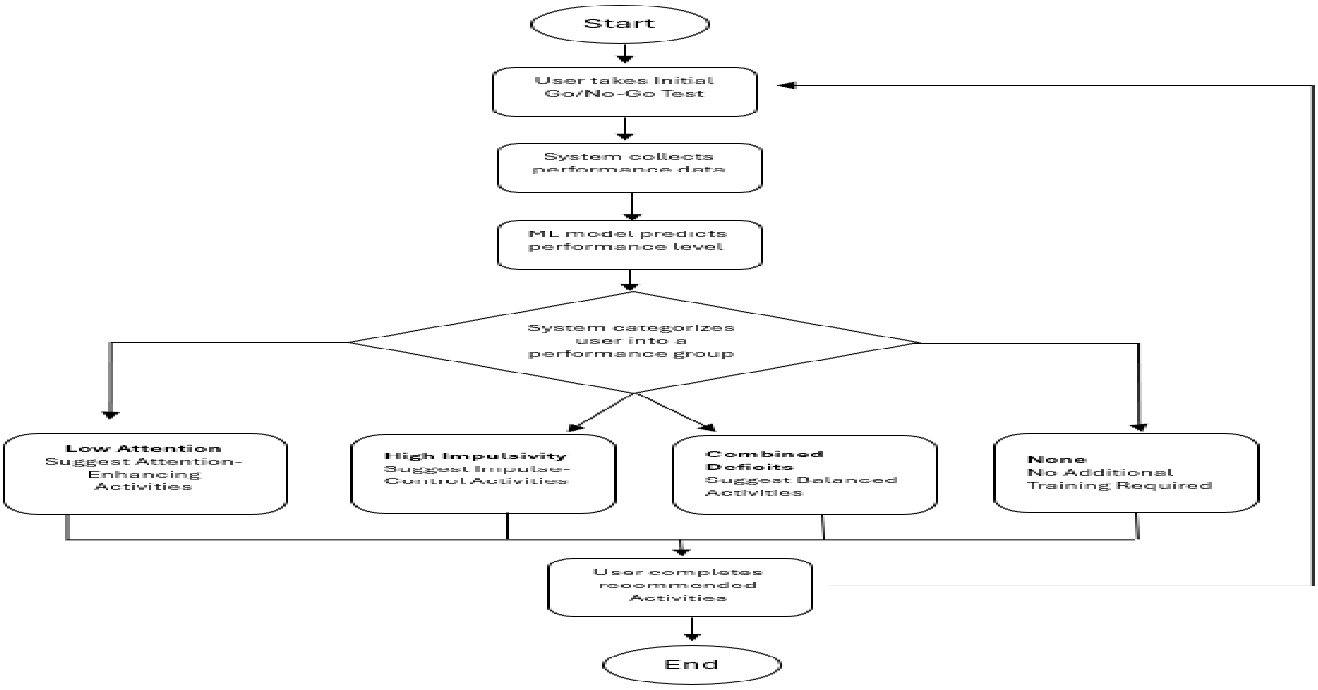

Figure 2: System workflow

As shown in Figure 2, the initial Go/No-Go test used for data collection and model training is integrated into the system to assess ADHD users' cognitive performance. When a user completes the initial Go/No-Go test, the system utilizes the trained Random Forest model to predict their performance level based on attention and impulsive metrics.

Based on the predicted performance level, the system recommends personalized Cognitive Improvement Activities, which consist of Go/No-Go tasks with varying levels of complexity. These tasks are designed to enhance attentional control and impulse regulation by gradually increasing difficulty based on the user's needs.

After completing the Cognitive Improvement Activities, users have the option to retake the initial Go/No-Go test to evaluate their progress and obtain an updated performance assessment. This iterative approach enables continuous monitoring and adaptive cognitive training, ensuring that activities are aligned with the user's evolving cognitive capabilities. Gamification elements such as earning points are integrated into cognitive activities to enhance engagement and motivation.

RESULTS AND DISCUSSIONS

Overview of Experimental Findings

The study aimed to develop a ML-based approach to recommend personalized cognitive activities based on performance in a computerized Go/No-Go task by using classification model. The classification results were used to suggest cognitive improvement activities tailored to individual performance metrics. One of objectives was to assess the effectiveness of different ML models in predicting ADHD-related cognitive performance based on reaction time, omission errors, and commission errors.

To evaluate the performance of the machine learning models, the dataset was split using the train-test split method, with 80% of the data used for training and 20% reserved for testing. This approach enabled a straightforward and efficient validation of each model's ability to generalize to unseen data. Three ML algorithms; Random Forest (RF), Gradient Boosting (GB), and Support Vector Machine (SVM) were tested for their ability to classify ADHD types. The performance of these models was evaluated based on accuracy rate. As shown in Table 2, the results indicated that Random Forest outperformed the other models with an accuracy of 92.73%, whereas Gradient Boosting and SVM exhibited significantly lower accuracy, rendering them unsuitable for further use.

Table 2: Model Performance Metrics

Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest Classifier	92.73	0.93	0.92	0.92
Gradient Boosting Classifier	89.76	0.90	0.89	0.89
Support Vector Machine (SVM)	86.30	0.86	0.85	0.85

Given these outcomes, Random Forest was selected as the optimal model for predicting cognitive performance levels. The superior performance of the Random Forest model can be attributed to its ability to handle non-linear relationships and high-dimensional data effectively. ADHD-related cognitive performance data exhibit high variability, and decision-tree-based models like Random Forest excel at capturing these intricate patterns through an ensemble approach.

Implications for ADHD cognitive performance levels Classification and Intervention

The findings highlight the effectiveness of using a machine-learning-based classification system in ADHD management. The ability of the Random Forest model to accurately predict ADHD cognitive performance levels enhances the potential for real-time intervention strategies. By leveraging CPT data, the system can dynamically categorize children into different cognitive performance levels, thereby facilitating personalized cognitive training programs.

A key contribution of this research is the integration of ML in ADHD intervention beyond mere classification. Unlike conventional studies that focus solely on diagnosis, this system incorporates predictive analytics to recommend targeted cognitive improvement activities. This approach ensures that each child receives tailored interventions based on their real-time performance, bridging the cognitive skill gap between ADHD and non-ADHD children.

Comparison

While previous studies have explored ML applications in ADHD detection, they primarily rely on questionnaire-based assessments from parents and teachers. These methods, while valuable, are inherently subjective and do not capture real-time cognitive responses. In contrast, this research leverages objective, task-based performance metrics obtained from CPTs, ensuring a more precise and data-driven approach to ADHD classification and intervention.

Additionally, the comparative approach where ADHD performance is evaluated against a non-ADHD baseline represents a novel advancement. Many existing studies fail to incorporate this direct comparison, limiting the ability to measure cognitive improvement effectively. By establishing a baseline from non-ADHD children and using it as a reference, this study ensures that cognitive interventions are aligned with developmental benchmarks, making them more impactful.

Limitations and Future Directions

While the study successfully demonstrated the feasibility of using ML models for ADHD classification, certain limitations exist. Firstly, the sample size for model training was limited, and larger datasets could improve model generalization. Secondly, while Random Forest achieved reasonable accuracy, future work could explore deep learning techniques that might further enhance classification performance. Another area for future research is expanding cognitive improvement activities beyond Go/No-Go tasks. Incorporating multimodal interventions, such as more gamified cognitive exercises and adaptive learning modules, could enhance engagement and long-term effectiveness.

CONCLUSION

This research successfully developed an AI-powered system that integrates CPT with ML to assess and improve cognitive performance in children with ADHD. By leveraging a computerized Go/No-Go task, we established a baseline for non-ADHD children and used this data to evaluate attentional control and impulsivity in ADHD participants. The deviations from this baseline allowed for the classification of ADHD children into distinct cognitive performance categories, enabling personalized cognitive intervention strategies.

Machine learning models, including Random Forest, Gradient Boosting, and Support Vector Machines (SVM), were tested for predicting ADHD children's cognitive performance based on the collected data. Among these, Random Forest demonstrated the highest accuracy (70%), while the other models proved unstable for reliable predictions. This finding reinforces the potential of ensemble-based models in ADHD classification and cognitive performance analysis.

One of the key contributions of this study is Unlike traditional ADHD assessments that rely primarily on subjective reports from parents and teachers, this system provides an objective, data-driven approach that dynamically tracks children's cognitive progress. Furthermore, the integration of personalized cognitive improvement activities ensures that interventions are tailored to individual needs, thereby enhancing attentional control and reducing impulsivity over time to bridge the cognitive skill gap between ADHD and Non- ADHD peers.

In conclusion, this study highlights the potential of integrating AI-driven assessments with personalized cognitive training to bridge the cognitive skill gap between ADHD and non-ADHD children. By leveraging machine learning to analyze performance metrics and suggest targeted interventions, this system provides a promising foundation for enhancing ADHD management in real-world educational and clinical settings.

REFERENCES

1. S. V. Faraone et al., "Attention-deficit/hyperactivity disorder," Nature Reviews Disease Primers, vol. 1, no. 1, pp. 15020, Aug. 2015, doi: 10.1038/nrdp.2015.20.
2. S. Sadr-Salek, A. P. Costa, and G. Steffgen, "Psychological Treatments for Hyperactivity and Impulsivity in Children with ADHD: A Narrative Review," Children, vol. 10, no. 10, p. 1613, Sep. 2023, doi: 10.3390/children10101613.
3. F. Somma, A. Rega, and O. Gigliotta, "Artificial intelligence-powered cognitive training applications for children with attention deficit hyperactivity disorder: a brief review," in Proc. 12th Int. Conf. Disability, Virtual Reality & Assoc. Technol., 2018, pp. 387–394.
4. J. N. Epstein et al., "Evidence for higher reaction time variability for children with ADHD on a range of cognitive tasks including CPT," J. Child Psychol. Psychiatry, vol. 44, no. 6, pp. 967–981, Sep. 2003.
5. C. Robledo-Castro, P. R. Lerma-Castaño, and G. Bonilla-Santos, "Effect of Cognitive Training Programs Based on Computer Systems on Executive Functions in Children With ADHD: A Systematic Review," Journal of Attention Disorders, vol. 27, no. 13, pp. 1467–1487, Nov. 2023, doi: 10.1177/10870547231187164.
6. M. Ghazisaeedi, L. Shahmoradi, S. R. Niakan Kalhori, and A. Bashiri, "Management of Computerized Cognitive Training Programs in Children with ADHD: The Effective Role of Decision Support Systems," Iranian Journal of Public Health, vol. 47, no. 10, pp. 1611–1612, Oct. 2018.
7. J. T. Shaffer, et al., "Enhancing attention through training: A review of the Play Attention system," Journal of Attention Disorders, vol. 22, no. 7, pp. 671-680, Jul. 2019. Available: 10.1177/1087054716667387.

8. N. Wrońska, B. Garcia-Zapirain, and A. Mendez-Zorrilla, "An iPad-Based Tool for Improving the Skills of Children with Attention Deficit Disorder," Int. J. Environ. Res. Public Health, vol. 12, pp. 6261-6280, Jun. 2015. DOI: 10.3390/ijerph120606261.
9. S. H. Kollins et al., "A novel digital intervention for actively reducing severity of paediatric ADHD (STARS-ADHD): a randomised controlled trial," The Lancet Digital Health, vol. 2, no. e168, pp. e168-e178, Apr. 2020. Available: 10.1016/S2589-7500(20)30017-0.
10. A. Thennakoon, D. Perera, S. Sugathapala, S. Weerasingha, P. Samarasinghe, D. Dahanayake, and V. Piyawardana, "Individualized Edutainment and Parent Supportive Tool for ADHD Children," in Proc. of the 2nd International Conference on Advancements in Computing (ICAC), Malabe, Sri Lanka, Dec. 2020.
11. P. Chatpreecha and S. Usanavasin, "Design of a Collaborative Knowledge Framework for Personalised Attention Deficit Hyperactivity Disorder Treatments," Journal of Healthcare Engineering, vol. 2023, Article ID 9876543, 18 pages, 2023. Available: 10.1155/2023/9876543.
12. B. D. Sandipa, D. M. Mitratne, M. D. A. Isurika, D. S. Kandanaarachchi, S. C. Rathnayaka, and W. W. Tissera, "Artificial Intelligence and Machine Learning Based Approach to Motivate and Assist Primary School ADHD Children," Int. Res. J. Innov. Eng. Technol., vol. 7, no. 9, pp. 89-96, Sep. 2023. Available: 10.47001/IRJIET/2023.709010.
13. M. C. Miranda et al., "Performance patterns in Conners’ CPT among children with attention deficit hyperactivity disorder and dyslexia," Arq Neuropsiquiatr, vol. 70, no. 2, pp. 91-96, 2012. [Online]. Available: 10.1007/s00415-012-6638-5.
14. O. Slobodin, I. Yahav, and I. Berger, "A Machine-Based Prediction Model of ADHD Using CPT Data," Front. Hum. Neurosci., vol. 14, Article ID 560021, Sep. 2020. DOI: 10.3389/fnhum.2020.560021.
15. S. Bezdjian, L. A. Baker, D. I. Lozano, and A. Raine, "Assessing inattention and impulsivity in children during the Go/No-Go task," British Journal of Developmental Psychology, vol. 27, no. 2, pp. 365–383, Jun. 2009, doi: 10.1348/026151008X314919.
16. Centers for Disease Control and Prevention (CDC), "Data and Statistics on Children’s Mental Health," CDC, 2022. [Online]. Available: https://www.cdc.gov/childrensmentalhealth/data.html.
17. S. R. Pliszka, "Pharmacologic treatment of attention-deficit/hyperactivity disorder: efficacy, safety, and mechanisms of action," Neuropsychology Review, vol. 17, no. 1, pp. 61-72, 2007.
18. K. M. Antshel and R. A. Barkley, "Adolescent ADHD and its treatment," Adolescent Psychiatry, vol. 31, no. 1, pp. 42-56, 2008.
19. S. M. Eyberg and B. W. Funderburk, "Parent-Child Interaction Therapy: An evidence-based treatment for children's behavior problems," Journal of Clinical Child & Adolescent Psychology, vol. 40, no. 2, pp. 87-98, 2011
20. O. I. Lovaas, "Early and intensive behavioral intervention in autism," Journal of Developmental and Behavioral Pediatrics, vol. 24, no. 2, pp. 105-113, 2003.
21. **MTA Cooperative Group**, "A multi-site, randomized, controlled trial of treatment strategies for attention-deficit/hyperactivity disorder," The Journal of the American Medical Association (JAMA), vol. 279, no. 14, pp. 1100-1107, 1999.