PULSEMIND: AI-DRIVEN BEHAVIORAL ASSESSMENT AND INTERVENTION FOR ADHD

Dharmasena U.D.S.V.

IT21288326

Dissertation submitted in partial fulfillment of the requirements for the Bachelor of Science (Hons) in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

April 2025

PULSEMIND: AI-DRIVEN BEHAVIORAL ASSESSMENT AND INTERVENTION FOR ADHD

Dharmasena U.D.S.V.

IT21288326

BSc (Hons) degree in Information Technology Specializing in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

April 2025

DECLARATION

I declare that this is my own work, and this dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. Also, I hereby grant to Sri Lanka Institute of Information Technology the non-exclusive right to reproduce and distribute my dissertation in whole or part in print, electronic, or other medium. I retain the right to use this content in whole or part in future works (such as articles or books).

Student Name	Student ID	Signature
Dharmasena U.D.S.V.	IT21288326	

The above candidate has conducted research for the bachelor’s degree Dissertation under my supervision.

Signature of the Supervisor: Date

ACKNOWLEDGEMENT

Primarily, I would like to express my sincere gratitude to my supervisor, Dr. Sanvitha Kasthuriarachchi, for her invaluable guidance, encouragement, and continuous support throughout the course of this research. Her expertise and insightful feedback have been fundamental to the development and success of this project.

I am also deeply grateful to my co-supervisor, Ms. Mihiri Samaraweera, for her constant support, constructive advice, and thoughtful suggestions, which helped me navigate various challenges during the research process.

A special note of appreciation goes to Dr. Kamalani Wanigasinghe, Consultant Pediatric Neurologist at the Senehasa Research Centre, for her expert insights and valuable contributions as the external supervisor. Her guidance was instrumental in shaping the medical and clinical aspects of this ADHD assessment research.

I extend my heartfelt thanks to the teachers, parents, and students of Little Rose Preschool, whose participation and cooperation were vital during the data collection and application testing phases. Their support made a significant impact on the success of this study.

I would also like to thank my project team members for their collaboration, dedication, and commitment throughout the project. As the team leader, I am truly appreciative of their efforts and the collective contribution that helped bring this research to life.

Lastly, I wish to acknowledge all those who supported and encouraged me throughout this journey, directly or indirectly. Your support has been appreciated.

ABSTRACT

PulseMind offers an artificial intelligence-driven, gamified evaluation platform that aims to improve the early identification and subtype discrimination of Attention-Deficit/Hyperactivity Disorder (ADHD) in children between the ages of 5 and 10 years old. The research overcomes the shortcomings of conventional ADHD diagnosis, frequently subjective, lengthy, and culture discordant, by integrating real-time behavior data from a reaction-time video game with parent-reported symptoms via a DSM-5-based adaptive questionnaire. It measures digital biomarkers like reaction time variability, impulsive, and sustained attention, which are then analyzed by a neural network to categorize ADHD into inattentive, hyperactive-impulsive, or combined subtypes. Piloted with 62 children, PulseMind recorded 84.3% classification accuracy and enhanced user engagement, at a 94.3% game completion rate and parental usability scores. Its approach to data fusion, cultural adaptation for Sri Lanka, and the inclusion of personalized intervention modules position PulseMind as a scalable, clinically practical tool for early ADHD screening and intervention. This research validates the feasibility and efficacy of combining machine learning, gamification, and adaptive testing in digital mental health assessment for children

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ADHD	Attention-Deficit/Hyperactivity Disorder
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
ML	Machine Learning
VADPRS	Vanderbilt ADHD Diagnostic Parent Rating Scale
CD	Conduct Disorder
ODD	Oppositional Defiant Disorder
CPT	Continuous Performance Test
CANTAB	Cambridge Neuropsychological Test Automated Battery
API	Application Programming Interface
SUS	System Usability Scale
UI	User Interface
CSV	Comma-Separated Values
SD	Standard Deviation
SVM	Support Vector Machine
HIPAA	Health Insurance Portability and Accountability Act
GDPR	General Data Protection Regulation

1. INTRODUCTION

Attention-deficit hyperactivity disorder has been defined and described as a neurodevelopmental disorder of about five to eight percent of every hundred children attending school across the world [1]. Reduced symptoms of inattention, hyperactivity, and impulsiveness affect the ability of the child to function effectively in a variety of settings, including academic, social, and everyday activities [2]. Early recognition and effective intervention enable a child with ADHD to develop skills in coping with the disorder, which eventually improves the quality of life [3].

Such symptoms continue into distinct stages of development and, if not addressed, may lead to possible adverse long-term effects [4]. In low and middle-income countries, including Sri Lanka, people are not even aware of the existing assessment and management schemes for ADHD. Thus, there is an urgent need for culturally adapted and accessible diagnostic and intervention instruments. Early intervention or management during the primary time at school is especially important because it would avoid the consequences of failing to recognize ADHD in the early stages, including its effects, such as academic failure, social withdrawal, and a sense of low self-esteem [5].

The present study describes an innovative approach for the early diagnosis of ADHD using a software-based system that comprises a game-like behavioral task and an adaptive questionnaire, both built on the DSM-5 diagnostic criteria for ADHD. The gamified task relates to the cognitive domains of inattention and impulse control. The adaptive questionnaire, on the other hand, adds value to established tools like the Vanderbilt ADHD Diagnostic Parent Rating Scale and Conners' Rating Scale for more exhaustive and individualized evaluation [6] [7].

It increases the level of involvement and the accuracy of detection of symptoms for educators, caregivers, and healthcare professionals [8]. The interactive game shows children a number of visual and auditory stimuli and then allows researchers to measure such qualities as attention, impulsiveness, and hyperactivity based on reaction times and sustained attention. Such behavioral measures are valuable in identifying certain symptoms related to the ADHD disorder that may be troubling the child.

At the end of the game, the subjects take an adaptive questionnaire, which modifies its contents according to their answers, thus providing a tailored and in-depth assessment. This modality is consistent with previous work promoting gamification to enhance interest and improve diagnostic results [8]. The application uses machine learning algorithms to analyze the gathered data, which will then be used to classify children into specific ADHD subtypes, thus providing a more comprehensive view of the symptom profiles they exhibit [9]. Such automated classification promotes an attendant, tailored intervention and lightens the load in a traditional health care system. In addition, machine learning increases the accuracy of the tool with time as it learns continuously.

1.1. Background Literature

ADHD evaluation is a systematic, multi-method procedure for using various important inputs from informants such as parents, teachers, and healthcare professionals [10]. The American Psychiatric Association, entitled the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) the major reference in clinical practice for the diagnosis of ADHD [11]. ADHD is classified among the neurodevelopmental disorders as a persistent pattern of inattention and/or hyperactivity-impulsivity that hinders the developmental process along with daily living [12] [13] [14].

Criteria for ADHD according to DSM-5

ADHD symptoms are classified into two main groups according to DSM-5, that is, Inattention and Hyperactivity-Impulsivity. To diagnose the condition, symptoms must be present in at least two settings, such as home and school, and must have a significant effect on the social, academic, or occupational functioning. The individual's symptoms must not be explained better by another mental disorder as well [15].

- Inattention: This includes nine symptoms, which are failing to pay close attention, having trouble sustaining attention, making frequent careless mistakes, and losing necessary items. Six symptoms from this group should be present for children less than 16; if the person is seventeen or older, then five symptoms should be present [16].
- Hyperactivity-Impulsivity: This type comprises nine symptoms, including fidgeting, inappropriate leaving of one's seat, talking too much, difficulty waiting for one's turn, and interruption [16] [17] [18].
- Additional Diagnostic Requirements: The symptoms should develop before the age of twelve, last for at least six months, and affect the ability to function [17].

1.1.1. Clinical interview and rating scale approaches

Databases in which the clinician uses the DSM-5 for systematic diagnosis of ADHD provide diagnostic integrity [18]. Although structured interviews, behavioral observations, and standardized rating scales (e.g., Conners' Rating Scales and ADHD Rating Scale IV) are still quite popular, they aren't always without shortcomings, especially in subjective reports and individual variation with context at times, like in an observational setting such as school [19].

Name of tools by author(s)	Year published	Normative data by age	Cost
Specific/narrow-band			
ADHD-RS-V by DuPaul *et al.*	2016	5 to 18 years	$
ADDeS-4 by McCarney and Arthaud	2013	4 to 18 years	$
CRS-3 by Conners	2008	3 to 18 years	$
		Self-report (12–18 years)	
SNAP by Swanson	2007	5 to 11 years	Free
CAT-C by Bracken and Boatwright	2007	8 to 18 years	$
VARS by [1]NICHQ	2002	6 to 12 years	Free
BADDS by Brown	1996 & 2001	Preschooler (3–7 years)	$
		School-age (8–12 years)	
		Adolescent (12–18 years)	
		Adult (≥18 years)	
		Self-report (>12 years)	
SKAMP by Swanson *et al.*	1992	7 to 12 years	$
ACTeRS by Ullman *et al.*	1986	4 to 14 years	$
Global/broadband			
BASC-3 by Reynold and Kamphaus	2015	2 to 21 years	$
Achenbach/CBCL by Achenbach	2001	6 to 18 years	Free

Figure 1-1.1 ADHD assessment tools and rating scales

Tools validated in various age groups to assess ADHD symptomatology exist. For example, the Dutch version of the ADHD Rating Scale Revised and the Conners Adult/Children ADHD Rating Scales (CRS-3) differ from one another in applicability by age and their cost, allowing practitioners to select appropriate methods based on developmental needs and resources available [20].

Such diagnostic tools define the importance of standardized, age-appropriate assessments. They also open avenues for futuristic, modern, and technology-based means, such as web platforms and mobile applications testing.

Vanderbilt ADHD diagnostic parent rating scale (VADPRS)

In this research project, VADPRS serves as a primary screening instrument. VADPRS was developed by the American Academy of Pediatrics for parents or caregivers of children aged 6 to 12 years, but is often used for ages 5 to 15 [21]. The fifty-five items assess ADHD symptoms, oppositional defiance (ODD), conduct disorder (CD), anxiety, depression, and academic performance [22].

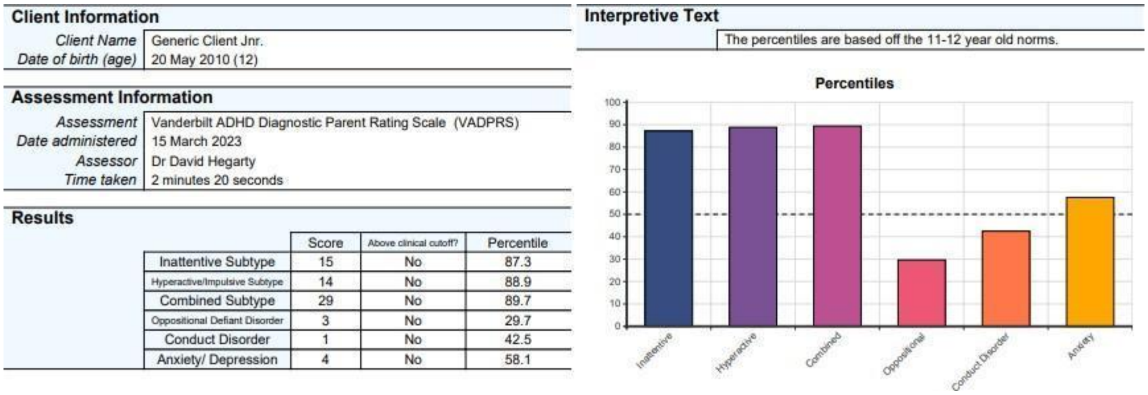
Structure of the VADPRS

Two main parts characterized the VADPRS:

- ADHD Symptom Criteria: The first eighteen items will be referred to the DSM-5 ADHD criteria. Of these, two subscales- nine items for inattention, and the other nine items for hyperactivity and impulsivity. According to DSM-5, this must be at least six symptoms in either category for children under seventeen [23].
- Performance and Behavioral Assessment: This segment provides information about academic performance and associated behavioral problems such as oppositionality, conduct problems, and mood symptoms, aiding clinicians in understanding the child's broader behavioral and emotional context [24].

		Never	Occasionally	Often	Very Often
1	Does not pay attention to details or makes careless mistakes, for example homework	0	1	2	3
2	Has difficulty attending to what needs to be done	0	1	2	3
3	Does not seem to listen when spoken to directly	0	1	2	3
4	Does not follow through when given directions and fails to finish things	0	1	2	3
5	Has difficulty organizing tasks and activities	0	1	2	3
6	Avoids, dislikes, or does not want to start tasks that require ongoing mental effort	0	1	2	3
7	Loses things needed for tasks or activities (assignments, pencils, books)	0	1	2	3
8	Is easily distracted by noises or other things	0	1	2	3
9	Is forgetful in daily activities	0	1	2	3
10	Fidgets with hands or feet or squirms in seat	0	1	2	3

Figure 1-2 Sample questions from the VADPRS



Client Information

Client Name	Generic Client Jnr.
Date of birth (age)	20 May 2010 (12)

Assessment Information

Assessment	Vanderbilt ADHD Diagnostic Parent Rating Scale (VADPRS)
Date administered	15 March 2023
Assessor	Dr David Hegarty
Time taken	2 minutes 20 seconds

Results

	Score	Above clinical cutoff?	Percentile
Inattentive Subtype	15	No	87.3
Hyperactive/Impulsive Subtype	14	No	88.9
Combined Subtype	29	No	89.7
Oppositional Defiant Disorder	3	No	29.7
Conduct Disorder	1	No	42.5
Anxiety/ Depression	4	No	58.1

Interpretive Text

The percentiles are based off the 11-12 year old norms.

Figure 1-3 Sample results for a 12-year-old child

A 12-month-old sample VADPRS result may typically have something as below:

- Inattentive subtype: Six or more "Often" or "Very Often" ratings on items 1-9 with performance concerns on items 48-55.
- Hyperactive/Impulsive subtype: Six or more "Often" or "Very Often" ratings on items 10-18, with performance problems also noted.
- Combined subtype: Satisfies criteria for both inattention and hyperactivity/impulsivity.
- Comorbid Concerns: High scores on the relevant items may indicate other problems like
    - ODD: Four or more symptoms rated 2 or 3 on items 19–26 with performance impairment.
    - CD: Three or more symptoms rated 2 or 3 on items 27-40.
    - Anxiety/Depression: Three or more items scored 2 or 3 on questions 41-47, with associated performance issues.

Scores will also be given as percentiles compared with a community sample, with higher scores meaning more severe problems [25].

Advantages of VADPRS versus other scales

Compared to other rating tools like the Conners' Rating Scale or ADHD Rating Scale IV [26], the VADPRS gives many advantages [27] [28]:

- Overall Evaluation: Besides assessing core ADHD symptoms, it also assesses academic performance and potential comorbid conditions, which are frequently encountered in the ADHD population.
- Parental Involvement: Completed by caregivers, the scale gives essential information about children's everyday behavior.
- DSM-5 Conformity: The whole structure closely resembles the DSM-5 criteria for diagnosis, thereby improving the clinical utility.

In conclusion, VADPRS is an efficient diagnostic tool for children aged 5-15. However, for a complete, multi-faceted view of the functioning of the child, it must be kept along with the teacher reports and structured interviews.

1.1.2. The role of technology in ADHD assessment

Newer technologies are needed for the development of new assessment approaches for ADHD, preparing to banish the limitations of traditional methods. Some of these newer assessment methods are computerized neuropsychological tests, game-based assessments, mobile technologies, machine learning applications, and a combination of digital parent reporting.

Computerized neuropsychological tests

Digital modifications to traditional neuropsychological assessments have led to standardization, accessibility, and cost-effectiveness. Platforms such as the NIH Toolbox Cognition Battery, Cambridge Neuropsychological Test Automated Battery (CANTAB), and assorted computerized continuous performance tests (CPTs) offer automated testing and scoring, which minimizes examiner bias and human error [29] [30]. Such computerized tools correlate moderately to strongly (r=0.65-0.85) with their traditional counterparts while shortening the time taken for test administration by about 30-40% [30]. With all these apparent advantages, the computerized therefore retain the artificial and controlled nature of traditional testing situations, thereby potentially limiting the advancement of ecological validity.

Game-based assessment.

Game-based assessments provide a way of conducting cognitive and behavioral assessments in a new format that associates them with the fun environment of a game. The application thereby uses intrinsic reward mechanisms to enhance engagement, which is critical for the ADHD population, while collecting performance characteristics that can be regarded as digital biomarkers [31] [32].

Such improvement has been evidenced by studies comparing the performance of ADHD and control groups with game-based tools [34]. For instance, the very recently approved EndeavorRx (formerly Project EVO) received FDA clearance as an effective digital therapeutic for ADHD, thus proving its clinical value. [34].

Key advantages of game-based assessments include:

- Enhanced engagement: Gamification sustains attention and motivation more effectively than traditional assessments, potentially improving data reliability.
- Multidimensional measurement: Games allow simultaneous tracking of variables like response time variability, error patterns, learning curves, and strategic decision-making.
- Reduced test anxiety: Framing assessments as gameplay may decrease performance-related stress.
- Remote administration potential: Many tools are deployable via mobile devices, increasing accessibility for underserved populations.

However, these tools vary widely in development quality and psychometric rigor. Many were designed primarily for engagement rather than precise measurement, limiting their diagnostic utility (Davis et al., 2018) [33].

Machine learning applications

Machine learning (ML) has the unique ability to identify and delineate complex patterns from behavioral and cognitive data, thus outperforming classical classification algorithms. Several studies report classification accuracies well over 80%, based on various combinations of digital performance metrics [35] [36]. Using a careful combination of cognitive performance, movement patterns, and physiological signals, ML models can establish novel digital biomarkers of ADHD while facilitating the tailoring of assessment profiles. However, current applications are constrained by small datasets, a lack of interpretability, and low generalizability.

Integration of parental reports with digital assessment

When combining standardized parent-report questionnaires with objective digital assessments, the result is a more comprehensive approach. Digital versions of assessment tools-such as the Vanderbilt ADHD Diagnostic Rating Scale-have various advantages:

- **Accessibility**: Given that parents can complete the assessments from home, this reduces the logistical burden.
- **Automatic scoring**: The immediate computation of results and comparison with normative data further expedites the assessment process.
- **Data integration**: Digital platforms can merge subjective accounts such as parent reports with objective performance data to gain more clinical insight.
- **Long-term monitoring**: Electronic systems allow for easy tracking of hemorrhaging symptoms over time and treatments.

Digital parent-report systems tend to be as dependable as paper formats (α=0.78-0.89) while reducing completion time by 25% and scoring errors [37]. However, they still carry important disadvantages inherent in conventional scales, such as reporter bias and cultural differences in the interpretation of symptoms.

1.2. Research Gap

Research A: The referred studies followed the design of employing a game involved in a mobile application for the ML-based early diagnosis of ADHD among the children in Sri Lanka. This application showed the possibility of solving accessibility difficulties and enhancing ADHD recognition and control via exciting, dynamic learning activities. However, the study focused on strengthening a set of cognitive skills, including attention and concentration, and did not include a generalized procedure for subtype identification or integration of multiple data inputs. In addition, it stressed prospects as the subject of future developments of the app for the expansion of the list of symptoms of ADHD and the addition of sections for constant monitoring and management, as well as there is potential for further development in real-time symptom tracking analysis and personalization of individualized interventions [38].

However, our research extends these gaps by proposing a gamified ADHD assessment system that is intentionally created for the purpose of framing subtype assessments (inattentive, hyperactive-impulsive, combined) and the fusion of multiple data components, such as parents' comments on their child's behavior and behavior metrics gathered from the game. Though the application works on the treatment through games, our system is designed to identify clinical-grade diagnoses following DSM-5. The falling star reaction time game records reaction time, impulsive, and attention of a child, which when combined with the adaptive questionnaires and AI analysis, guarantees accurate classification of subtypes. Also, our studies concern the process of monitoring by including Intervention Modules related to the subtypes of ADHD throughout the accuracy for diagnosing and managing. Our system provided extensions to cater to the gaps identified in the study; the proposed system increases the scalability and the applicability within Sri Lankan clinical practice.

Research B: The mentioned study uses the decision tree algorithm for diagnosing ADHD and its subtypes based on behavioral/ neuropsychological/ electrophysiological data with high accuracy. Nevertheless, this study shows that machine learning can be used in ADHD diagnosis, but it employs and compares highly cost- and time-consuming methods based on EEG and the IVA test. These are cumbersome techniques, which demand equipment, clinics, and personnel that are not easily accessible, especially in the developing nations. Moreover, the approach uses a static database without the ensuing behavioral interaction or culturally sensitive instruments for the development of children in natural environments [39].

However, the present study aims to fill these gaps by proposing an easy-to-use, culturally appropriate, gamified Primary school ADHD screening mechanism for the Sri Lankan context. Playfully, our system thus collects real-time behavioral data concerned with attention, impulsiveness, and reaction time during the falling star reaction time game. The system combines this data with DSM-5-based adaptive parent questionnaires and utilizes AI-based data fusion; the system can diagnose sparse ADHD subtypes with clinical accuracy, all through the Smartphone, without the use of any specific equipment. This makes it even possible in low-resource environments. The above forms the basis for my proposed conceptual framework as a theoretical foundation for telehealth solutions in low-resource environments. Furthermore, for the cultural fit and universality of the method, as well as for its applicability for children, the system is similarly developed to be child-oriented, scalable, and interoperable, filling in the gap between intensive clinical assessment and fast, accurate, easy-to-use quick diagnostic and intervention tools.

Research C: The above-mentioned study sheds light on the limitations of Mobile Apps for parents with ADHD in children, stating that the apps do not have scientifically proven features, more features, or tools useful for monitoring the symptoms in real-time, and useful integrated tools for the parents to make an effective decision. While it serves as a reminder that apps must be designed with ADHD focused issues, it does not incorporate technological advances [40].

To this end, our study fills the gap by using more sophisticated machine learning techniques, including the decision tree and ensemble method, deemed to classify the ADHD subtypes, based on the behavioral data gathered from a game-based questionnaire. This module effectively tracks features such as attention level and response rate as well as impulsiveness in an entertaining way. Further still, the adaptive questionnaire is formed in DSM-5; more features are added according to the data obtained from children's behavior now of the application. By including the above elements and using the data fusion techniques, we combine the behavioral task results and parental feedback, our system offers an accurate, complete, and dynamic diagnostic approach that we think remarkably improves ADHD assistance from previous tools.

Research D: The referenced study discusses the various technological implementations of self-regulatory strategies of behaviors and emotions of children with ADHD; the described technological interfaces include wearables, augmented reality, and robots. Nonetheless, on average, many technologies are developed up to the prototype level or at pre-implementation pilot stage with limited integration within live settings. For the discussed technologies in the reviewed articles, enhancing self-regulation seems to be a potential view of innovative technologies, but what has been researched mainly comprises the outside objects rather than the informative paradigm of how the diagnostic and therapeutic systems could be integrated in a more holistic, individualized, and dynamic manner [41].

This study complements current research in that it goes beyond developing a prototype to make a concept a reality. It combines machine learning supported multimodal data analysis with a motivating and dynamic behavioral assessment instrument for the continuous assessment of attention and impulsivity. In contrast to other available tools, we use dynamic DSM-5-based questioners designed according to the specifics of symptoms and performance for obtaining accurate results. Moreover, by applying a gamification approach and data fusion techniques, the gap between entertaining interventions and evidence-based solutions is bridged by using input from children's behaviors and parental feedback. This offers an efficient, large-scale applicable diagnostic and therapeutic model of ADHD that is beyond self-regulation concepts for a more clinically oriented approach.

Table 1-1 Compare the proposed system with existing systems.

Feature	A [35]	B [36]	C [37]	D [38]	Proposed System
Use of gamification	✓ Yes, but dynamic learning activities	✗	✗	✗	Falling Star Reaction Time game tailored for subtype assessment and data collection.

Cultural appropriateness	✗	✓	✗	✗	Developed specifically for the Sri Lankan context.
Subtype identification	✗	✗	✓ But limited in generalization	✗	Gamified subtype-specific assessment (inattentive, hyperactive-impulsive, combined) using DSM-5 framework.
Integration of multiple data inputs	✗	✗	✗	✗	Real-time behavioral data (reaction time, attention, impulsivity) fused with adaptive. parental input.
Personalization and real-time monitoring	✗	✗	✗	✗	Personalized interventions based on real-time symptom tracking and data fusion techniques.
Intervention modules	✗	✗	✗	✗	Includes specific subtypes. intervention modules alongside diagnosis.
DSM-5 compliance	✗	✗	✓ Focus on machine. learning- based. methods but lacks DSM-5 compliance.	✗	Fully DSM-5-compliant Assessment and diagnosis system.

1.3. Research Problem

ADHD refers to one of the most common neurodevelopmental disorders in childhood, presenting with symptoms of hyperactivity, impulsivity, and inattention [20]. These symptoms usually interfere with academic performance, social life, and personal well-being [39]. Early identification and intervention are imperative; however, conventional assessment methods for ADHD face limitations, especially in the age group of children from 5 to 10 years.

Standard assessments are done based on subjective reports from parents or teachers, observation of clinical behavior, and self-report with long questionnaire instruments. All of these can be biased, time-consuming, and usually not geared toward engaging children's attention throughout the assessment process. Furthermore, they do not capture real-time behavior such as reaction time, sustained attention, or impulse control which are central to the symptoms of ADHD.

The main research question examined herein is the lack of fun, objective, and clinically relevant tool for assessing ADHD about the identification of its core symptoms and subtypes as they manifest among young children. Most instruments examined do not emphasize features such as real-time behavioral monitoring, gamification, or intelligent follow-up mechanisms facilitating symptom-specific responses based on diagnostic criteria.

Our study proposes the development of an AI-assisted, gamified assessment module that aligns with DSM-5 ADHD subtype criteria. At the heart of the system is a reaction-time game to assess the objective behavioral markers of premature responses, variability in reaction time, and sustained attention. The behavioral profile derived from the game triggers a dynamically generated questionnaire, completed by the parents, which is specific to the subtype of ADHD being evaluated, thereby enhancing diagnosis accuracy. The system amalgamates this dual data stream to ascertain which ADHD subtype is inattentive, hyperactive-impulsive, or combined.

The tool itself would be engaging for children, allowing for the collection of data on the child's symptoms without reliance on subjective recall or observation. After completion, the program also generates a feedback report for parents that summarizes symptoms endorsed by the child and gives practical suggestions for helping at home and school. This research thus aims to develop a scientifically sound, fast, and child-friendly intervention for assessing ADHD and planning early intervention by making a bridge between traditional measures and modern technology-enhanced tools.

1.4. Objectives

1.4.1. Main objective

To create an AI-based, game-inspired screening tool to assess children’s ADHD using real statistics according to DSM-5 and determine the type of ADHD (inattentive, hyperactive-impulsive, or combined) and provide feedback for the parents. It aims to improve the usability and utility for children and their families to help create the optimal climate for helping children with ADHD. Unlike a traditional behavioral survey that would seek to elicit certain responses from the parent and child, the integration of gamification will not only come up with data-oriented results in a fun and engaging way but will also provide information and advice for parents to act on, to modify the child’s behavior, and in the process be informative as well as functional.

1.4.2. Sub objectives

- **Design and implement a gamified ADHD assessment module.**

Make a serious, relatable, excitement-based falling star reaction time game that taps other important behavior information conditions, such as attention span, reaction time, and impulsiveness. Kids will behave 'normally' with amusing content, which makes this approach entertaining and free from stress while going through the assessment process. Presenting it at the primary school learning level.

- **Develop and deploy a standardized ADHD questionnaire system for parents.**

This will ensure that all participants have the same set of symptoms. This part of parental feedback will establish the ground to label each gaming session in terms of their respective ADHD type-inattentive, hyperactive-impulsive, or combined, with the child's game play data within a reliable dataset to train the prediction model.

- **Automate ADHD type labeling and continuous model retraining.**

Integrating the parent questionnaire responses with gameplay performance metrics for automatic labeling of game sessions with the ADHD type corresponding to the session. This data will be used to retrain the machine learning model and increase prediction accuracy over time. The system will evolve into itself, one that can identify an ADHD type more accurately based on gameplay, thus obviating the need for providing traditional questionnaires for future assessments.

- **Integrate multimodal data analysis for ADHD Type identification.**

A data fusion mechanism that integrates the game metrics and parent questionnaire data will be developed to indicate the presence or absence of ADHD-type characteristics. Machine learning techniques will study the variances in behavioral patterns as the basis for predicting the child's ADHD type. This makes it easier to assess each child's needs with a more dynamic, contextually aware, and personalized assessment process.

- **Create user-friendly interfaces for children and parents.**

Creation of straightforward, accessible child interfaces that minimize distraction and promote engagement would be undertaken. Icons, limited text, suitable imagery, voice options, and color adjustment will be proposed to cater to children with ADHD. A clear and intuitive interface would be available for parents to fill up the questionnaire with minimum complicated steps.

2. METHODOLOGY

2.1. Methodology

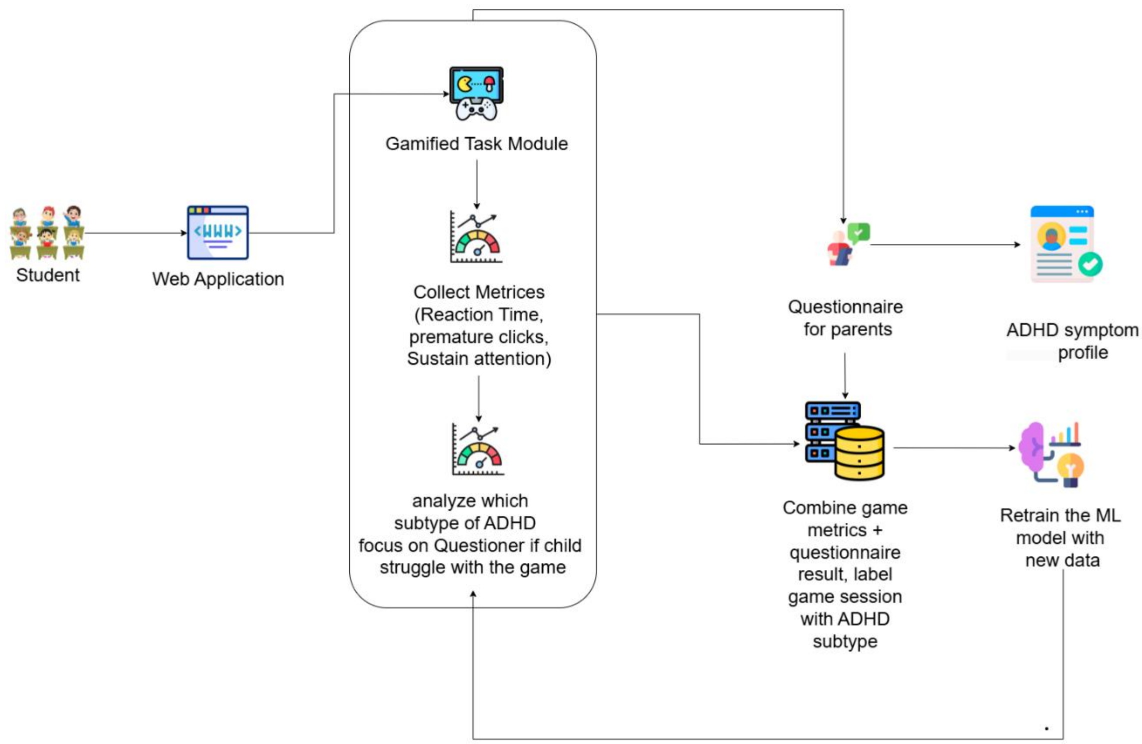


Figure 2-1 Component-specific system architecture diagram.

The Falling Star Game is a behavioral assessment tool that evaluates a child's attention span, impulse control, and consistency in responses during real-time navigation. The child is prompted to play with falling stars on the screen while disregarding distractions. During gameplay, performance metrics collected include:

- Reaction Times: Raw durations recorded for every user interaction to a given target.
- Reaction Time Variability: Reflects fluctuations in the responsiveness often linked to inconsistent attention.
- Average Reaction Time: The Mean response time, having a general slowness or over-responsiveness.
- Missed Star Streaks: Successive failures to interact with targets, thus indicating that there were lapses of or impaired attention.

- Click Timestamps: Detailed logs of each user action conducted, which are beneficial in the analysis of the timing and pattern of responses.
- Correct Streak: Longest string of correct actions without error, which indicates a sustained focus.
- Premature Clicks: Such actions are made before the target appears, indicating impulsiveness.
- Missed Stars: Count of total opportunities missed, which glances at inattentiveness.
- Aggregate Score: Runs a performance value summing up all tasks to give an idea of overall success in task performance.
- These metrics are then analyzed to detect different behavioral signatures related to ADHD subtypes. For instance:

    High prematurity in clicking counts with shorter yet inconsistent reaction times indicates hyperactive-impulsive behavior.

    Long reaction times and high missed stars or streak counts are indicative of inattentive behavior.

    Both patterns are typical of the combined ADHD subtype.

After the game session, parents are transitioned to the feedback module where they complete a standardized, DSM-based questionnaire. Unlike adaptive systems that would screen out and tailor questions, this one adopts the whole questionnaire, assuring consistent, comprehensive behavioral profiling. The questions are clear, culturally appropriate, and inoffensive, reflecting typical behaviors in everyday life.

This information is important since it brings in the child's home dimension, which complements the captured behaviors of that child while playing. Once both data streams are gathered, the system automatically labels the ADHD subtype according to combined results from both data streams. The labeled instances would be securely stored in the model with continuously built retraining pipelines to allow continuous refinement of the ADHD prediction model. Incrementally, as the dataset grows, the system becomes better at making ADHD subtype identification only from gameplay, while minimizing the use of any other questionnaire data in subsequent sessions. Combining behavioral data while playing games online with structured parent reports is meant to increase the reliability, accuracy, and personalization of assessing ADHD. It also controls the cultural and demographic applicability of the development and states its relevance for use within the primary school setting in Sri Lanka.

At the end of the assessment, a more comprehensive and user-friendly feedback report is generated. It will clearly define the behavioral indicators in the child, mention the predicted ADHD subtype, if any, and guide parents on how to manage noticed symptoms. The interface and content are designed to be easily interpretable, supportive, and actionable.

Briefly, this is an aspect of the research project applying gamification and machine learning in a new and pragmatic way to the detection of ADHD. Mixing entertaining game-based tasks and validated parental insights with automated learning systems gives greater access, objectivity, and cultural specificity in ADHD assessment. This will be a big milestone in the intervention of technology in behavioral health diagnostics.

2.2. Software Solution

2.2.1. Development process

Our development process follows the Agile methodology, which emphasizes flexibility, collaboration, and iterative progress. Unlike traditional, linear development models that rely on a fixed, sequential plan, Agile enables us to divide the work into smaller, manageable units known as sprints. This approach allows for continuous feedback, timely adjustments, and ongoing integration of changes throughout the project lifecycle, resulting in products that are more adaptable and aligned with user needs.

To support our Agile workflow, we utilize Microsoft Teams Planner as our task management tool. Planner enables our team to create, assign, and monitor tasks in an organized and visual format. Each sprint is mapped out within Planner using buckets and task cards, where team members can update progress, add comments, set priorities, and attach relevant documents. This promotes transparency, accountability, and collaboration among the team, ensuring that everyone stays aligned and informed throughout the development cycle.

By combining Agile practices with Planner's organizational features, we can maintain a clear structure while remaining adaptable to changes, delivering high-quality solutions in an efficient and user-centered manner.

2.2.2. Requirement gathering

- Interviews

Talk with Child Psychologists to elaborate on the symptom indicators and the diagnostic criteria. Interview the teachers as they can advise on the in-school behaviors that are relevant to this ADHD problem. The parents will be best placed to inform them regarding their experience with the assessment given to their children and what information would prove valuable.

- Surveys and Questionnaires

Quantitative data collection can be done by distributing surveys to parents and teachers. These would focus on the manifestation of ADHD symptoms in children. Surveys can also include questions to ask parents about the types of feedback that are useful and the extent of detail desired in the assessment results.

- Focus Groups

Conduct a focus group with parents, teachers, and child psychologists to identify the necessities of the assessment tool for ADHD. It can be used to confirm or refute first concepts, such as the falling star game idea, as well as which changes to the feature set or adjustments to the numbers would make it even more feasible and of higher diagnostic.

- Observational Studies

Trials per-formed with children playing with an early prototype of the game in 1-1 sessions. Pay attention to how they will respond to certain aspects of the game, whether they like it, and how they will respond to graphical or sound rewards. Also, pay attention to such points as whether it could create confusion or instabilities that would be used to help refine the surface of the user interface.

- Document Analysis

Analysis of the DSM-5 criteria in detail to find out the correlation between the features of the assessment and the standardized symptoms. Self-developed questionnaires, academic papers, clinical guidelines, and existing screening tools should be reviewed to have a clear picture of the frequently utilized techniques and indicators and therefore find out where this tool can provide a new or improved solution.

- Prototyping

Develop the Falling Star Game and parent feedback form on paper. These prototypes will be shared with a selected group of users, such as teachers and parents, for testing purposes and should solicit responses in terms of engagement, usability, and clarity. Refine the prototype based on suggestions provided by the users to make sure that the prototype meets the needs of the users.

2.3. Project Requirements

2.3.1. Functional requirements

- User profile management

The system shall enable the creation of accounts per child individually so that the child, the parent, or the guardian can log and monitor the child's gameplay over time.

- Gamified falling star activity for ADHD symptom assessment.
  The system shall include a falling star game in which children need to click on stars as they fall, implying forced attention and short response time. The game shall capture measures including reaction time (time taken to click on the star), temporal constancy (consistency in responding over time), and premature response clicking (response clicking before the star can be clicked). The system shall vary the speed and the frequency of the falling stars corresponding to the child in real time manner.

- Adaptive game flow
  The system should reduce the speed, duration, and the frequency of falling stars as it detects the child's reaction time and his/her ability to sustain on a particular level. This feature of the game shall enhance the learning process. If a child is performing well the game shall increase the speed of the stars; when the child is doing badly the game shall slow down the stars to get better.

- Parental and teacher input
  The system shall enable the parent and the teacher to enter observations about the behavior of the child outside the game environment, so the assessment is broader. This test is developed depending on the way child has played the game. Parents/teachers should supplement information given by the child to make the report more comprehensive on the child's attention and impulse control.

- Real-time feedback mechanism
  The system should inform the patient immediately that the right size is clicked through visual effects such as star emission when the correct size is clicked as well as sound emissions to determine the time factor involved. Any wrong or early click shall produce a polite beep or a visible signal to assist the child correct his or her timing.

- Machine learning-based analysis
  The system utilizes statistics and machine learning on the reaction time, consistent attention span, and early clicks of tasks, apparent behavioral signs of ADHD and from parents & teachers. According to the information gathered, it is expected that the system will generate the ADHD symptom profile concerning the identified subtypes.

- DSM-5 criteria alignment

  The falling star game shall be equated to DSM-5 criteria for ADHD by counting the number of times a participant clicked before it was their turn (impulsivity) and the number of times a participant missed their turn or lagged behind the others (inattention), as well as their performance during sustained attention assessments. The system should produce a report that will indicate how the child's game performance compares to DSM-5 criteria.

2.3.2. Non-functional requirements

- Performance

  According to the convenience of the game, the game shall be able to respond to the actions of the end user in less than few seconds. Users in the system shall be managed seamlessly in a way that will be, in either case, free from lag or interruption.

- Scalability

  The system's options shall allow for the extension to cater for more users at any given time as well as further features in assessment and reportage.

- Reliability

  The availability of this system should be at 99.9% to guarantee that both the game and the assessment features are always accessible. Perspective: All game data shall be saved automatically every minute for the purpose of protecting the data, should there be an abrupt shut down.

- Usability

  Further, it should be navigational for children between the ages of 5-10 and should contain basic controls and directions. This shall be facilitated using child-friendly icons and visuals.

- Compatibility

  Thereby, the system shall be compatible with a range of computing devices, mobile and stationery, with such OS as iOS and Android, and Microsoft Windows.

- Accessibility

  The game should thus comprise features for modified sound and graphics to suit the child with disabilities to play with children with other abilities.

- Maintainability

  The system should be constructed out of modules where changes to the code will be easily made on the module that requires the update.

2.3.3. Software requirements

Phaser (Game Development Framework)

- Application: Used to develop an interactive reaction-time game that measures key ADHD symptoms such as inattention and impulsivity.
- Features: Lightweight 2D engine supporting animations, event-driven logic, and customizable gameplay tailored for young users.
- Integration: Communicates with the Node.js backend to log real-time gameplay data, which influences adaptive task flows and personalized assessments.

Node.js (Primary Backend Framework)

- Application: Core backend system managing game responses, user session control, parental questionnaire delivery, and orchestration of assessment workflows.
- Features: High concurrency using event-driven architecture; enables seamless API integration with front-end and machine learning services.
- Integration: Connects to the Flask-based ML service for prediction and retraining, manages secure routing, and communicates with MongoDB for data storage.

MongoDB (Database)

- Application: Central data store for user profiles, game logs, DSM-5 questionnaire results, ADHD subtype labels, and model performance metadata.
- Features: Schema-flexible structure supports the evolving nature of behavioral and machine learning data. Enables efficient retrieval and filtering for analytics and model training.

React.js (Frontend Framework)

- Application: Builds dynamic UIs for children (game interface), parents (questionnaires and reports), and admins (dashboard).
- Features: Responsive design optimized for mobile and desktop. Utilizes real-time feedback, adaptive rendering of content, and interactive visualizations for monitoring.

Python with Flask (Machine Learning Microservice Framework)

- Application: A resolute microservice responsible for ADHD subtype prediction and retraining of machine learning models based on newly collected gameplay and questionnaire data. It also powers the model monitoring and lifecycle management dashboard.

- Features:

Hosts RESTful API endpoints for:

Prediction based on real-time game metrics and questionnaire responses.

Model retraining using newly labeled data.

Model replacement, updating the live model with a newly trained version.

Model health reporting, returning accuracy, performance metrics, and drift indicators.

Supports logging of retraining activity and version control for traceability.

Stores and serves model metadata (e.g., date trained, accuracy, dataset size) to the dashboard.

Dashboard Integration:

Communicates with a React-based ML Monitoring & Management Dashboard via secure API calls.

The dashboard displays:

Current model status and health (e.g., accuracy, F1 score, prediction distribution).

Retraining status and performance trends over time.

A button triggers retraining and deployment, which calls Flask's API to initiate training and dump the model for replacement.

Version history and logs to ensure transparency and rollback capability.

Enhances model governance, enabling data scientists or system administrators to manage the machine learning pipeline without needing to access the backend directly.

- Integration: Serves as a microservice accessed by the Node.js backend, which uses prediction results in real-time ADHD assessments and personalized feedback reports.

Algorithms

Machine Learning Models (via Flask Microservice)

- Models: Neural Network built using TensorFlow/Keras, trained on combined game performance metrics and parental questionnaire responses to classify ADHD subtypes (inattentive, hyperactive-impulsive, combined).
- Endpoints: /predict, /retrain, and /status for integration with Node.js backend and dashboard.

Rule-Based Task Difficulty Adjustment

- Predefined logic modifies in-game challenge levels based on user accuracy, reaction time, and impulsive indicators.

Performance Tracking and Statistical Analysis

- Tracks detailed behavioral metrics like missed stars, correct streaks, premature clicks, and attention lapses across sessions.
- Supports data visualization, personalized reporting, and continuous monitoring of symptom trends.

2.4. Commercialization Plan

Target market

- Primary Market:
  - Parents of children aged 5–10 in Sri Lanka (initial target)
  - Pediatricians, psychologists, and school counselors
  - Private and public educational institutions
  - Child mental health organizations
- Secondary Market:
  - South Asian countries with similar resource and cultural challenges
  - NGOs focused on neurodevelopmental disorders.
  - Telehealth and e-mental health platforms

Market needs and differentiation

- Current gaps: Lack of culturally adapted, objective, and engaging ADHD diagnostic tools.
- Unique value:
  - Gamified, kid-friendly experience
  - Real-time subtype prediction and adaptive questioning
  - Cultural tailoring for the Sri Lankan population
  - Integrated monitoring and retraining dashboard
  - Objective behavioral data (reaction time, impulse control) with parental insights

Revenue model

- Freemium + Subscription Model:

- Basic Tier (Free):
    - Game-based assessment.
    - Basic subtype report for parents
- Premium Tier (Monthly/Annual subscription):
    - Detailed analytics and comparison over time
    - Retraining capability and personalized insights
    - In-depth report for schools/clinicians
    - Priority support and feedback
- Institutional licensing:
    - Selling site licenses to schools, clinics, and hospitals
    - Volume discounts for NGOs or health ministries
- Partnership opportunities:
    - Partner with ed-tech or health-tech firms to integrate your system into their platforms.
    - Collaborate with universities or clinics for research-backed deployments.

Go-to-market strategy.

- Phase 1: Local pilot launch (Sri Lanka)
    - Collaborate with a small set of schools and pediatric clinics.
    - Run trials and collect feedback.
    - Engage local media for awareness and de-stigmatization campaigns.
- Phase 2: Wider regional expansion
    - Expand to more institutions and urban areas.
    - Translate and culturally adapt to Tamil and Sinhala
    - Begin outreach to nearby countries (India, Bangladesh, etc.)
- Phase 3: Global scale via digital channels
    - Launch online platform for broader international access.
    - Localize culturally and linguistically for other markets.
    - Expand AI capabilities based on region-specific data.

Marketing channels

- Digital Ads (Google/Facebook): Target parents, pediatricians, and educators
- SEO/Blogging: Build trust through ADHD awareness and education.
- Webinars: Host talks with experts on tech-assisted ADHD diagnosis
- Influencer/Education Partnerships: Collaborate with mental health advocates.
- Schools & Clinics: Distribute brochures and demo the tool in-person.

Scalability and future roadmap

- Cloud infrastructure: Use AWS/GCP for scalability
- Mobile app: Develop Android/iOS versions for broader reach.
- AI evolution: Incorporate reinforcement learning to improve game adaptation.
- Additional modules: Add intervention games and progress trackers.

Regulatory and compliance

- Ensure GDPR and HIPAA-aligned data handling.
- Seek ethical clearance for data collection and testing.
- Partner with clinicians for medical validation and support

Investment and funding

- Grants: Apply for innovation grants (WHO, UNICEF, ADB)
- Incubators: Join ed-tech or health-tech accelerators
- Seed Funding: Pitch to social impact investors and angel networks

2.5. Testing & Implementation

2.5.1. Implementation

1. Game architecture and development framework.

The *Star Catcher* reaction time game was developed using a combination of React and Phaser 3 to balance user interface flexibility with robust game mechanics. React was used to structure the user interface, managing different states of the game such as the start screen, gameplay HUD, and game over screen. These components allowed for clear separation of concerns and a smooth user experience. Phaser 3, on the other hand, managed the actual game logic, physics, and rendering, providing a high-performance environment for interactive elements and animations.

Figure 2-2 Reaction time game UI

The Phaser engine was integrated into the React application using a `ref`-based approach. This allowed the game canvas to be rendered within a React component without interfering with React rendering cycle. Phaser’s lifecycle methods - preload, create, and update - were used to load assets, initialize objects, and manage continuous updates such as animations and collisions.

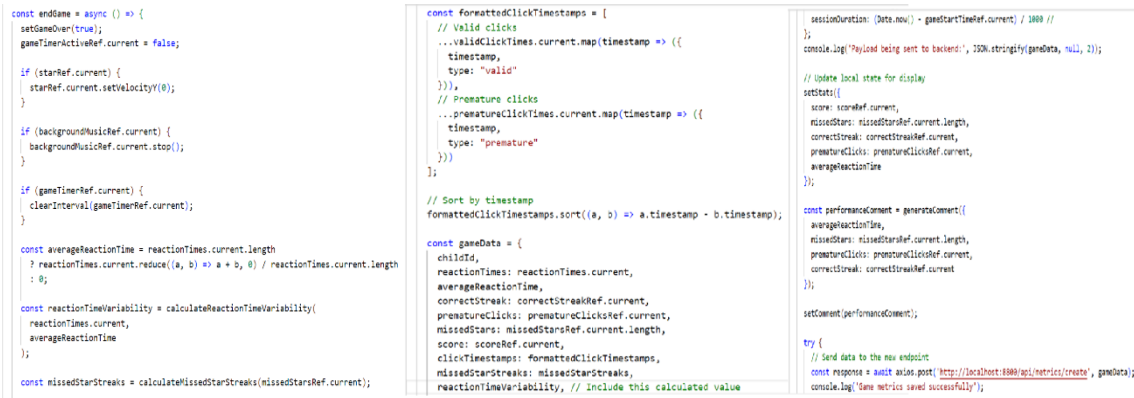
The core mechanic of the game involves stars falling from the top of the screen at random positions and varying speeds. Players interact with these objects by clicking on them with a mouse. There are two types of stars: regular stars worth one point and special golden stars worth five points. These stars are physics-enabled, allowing accurate movement and collision detection. Players are rewarded for timely clicks on stars, while premature clicks (when no star is present) and missed stars are recorded as negative indicators. The game includes a dynamic difficulty adjustment system that increases the falling speed of stars after every five successful consecutive catches, helping to tailor the challenge to the player's skill level.

To enhance engagement, various visual and audio elements were incorporated. The game includes a sky-themed background, animated stars, and distraction elements like meteors and fireballs. A custom cursor helps improve targeting precision. Audio feedback, such as background music and click sounds, reinforces player actions and enhances immersion. All sounds are managed using Phaser’s audio system.

```javascript
function handleStarClick(pointer, clickedStar) {
  if (!clickedStar || clickedStar !== starRef.current) return;

  const clickTimestamp = Date.now();
  const reactionTime = clickTimestamp - starAppearTimeRef.current;

  reactionTimes.current.push(reactionTime);
  validClickTimes.current.push(clickTimestamp); // Store valid click timestamp
  starResponseLogs.current.push({
    event: 'clicked',
    reactionTime,
    timestamp: clickTimestamp
  });

  correctStreakRef.current++;

  if (correctStreakRef.current === 5) {
    displayInGameComment("Nice! 5 in a row!");
  } else if (correctStreakRef.current === 10) {
    displayInGameComment("Great job! 10 streak!");
  } else if (correctStreakRef.current === 15) {
    displayInGameComment("Amazing! 15 streak!");
  } else if (correctStreakRef.current % 20 === 0) {
    displayInGameComment(`Incredible! ${correctStreakRef.current} streak!`);
  }

    // Add reaction time comments
    if (reactionTime < 300) {
      displayInGameComment("Lightning fast!");
    } else if (reactionTime < 500) {
      displayInGameComment("Great reflexes!");
    }

  if (correctStreakRef.current % 5 === 0) {
    speedDownRef.current += speedDownIncrement;
  }

  scoreRef.current += 1;
  setScore(scoreRef.current);

  resetStar();
}
```

Figure 2-3 Dynamic changes in the game according to player action

Feedback during gameplay is provided through both visual and textual means. Real-time comments such as “Nice! 5 in a row!” or “Careful! Wait for the star to appear!” help guide and motivate the player. As time runs out, the countdown timer changes color to red, alerting the player visually. At the end of a session, a summary screen displays performance metrics, streak information, and motivational commentary using emoji indicators.



```
const endGame = async () => {
  setGameOver(true);
  gameTimerActiveRef.current = false;

  if (starRef.current) {
    starRef.current.setVelocityY(0);
  }

  if (backgroundMusicRef.current) {
    backgroundMusicRef.current.stop();
  }

  if (gameTimerRef.current) {
    clearInterval(gameTimerRef.current);
  }

  const averageReactionTime = reactionTimes.current.length
    ? reactionTimes.current.reduce((a, b) => a + b, 0) / reactionTimes.current.length
    : 0;

  const reactionTimeVariability = calculateReactionTimeVariability(
    reactionTimes.current,
    averageReactionTime
  );

  const missedStarStreaks = calculateMissedStarStreaks(missedStarsRef.current);
```

```
  const formattedClickTimestamps = [
    // Valid clicks
    ...validClickTimes.current.map(timestamp => ({
      timestamp,
      type: "valid"
    })),
    // Premature clicks
    ...prematureClickTimes.current.map(timestamp => ({
      timestamp,
      type: "premature"
    }))
  ];

  // Sort by timestamp
  formattedClickTimestamps.sort((a, b) => a.timestamp - b.timestamp);

  const gameData = {
    childId,
    reactionTimes: reactionTimes.current,
    averageReactionTime,
    correctStreak: correctStreakRef.current,
    prematureClicks: prematureClicksRef.current,
    missedStars: missedStarsRef.current.length,
    score: scoreRef.current,
    clickTimestamps: formattedClickTimestamps,
    missedStarStreaks: missedStarStreaks,
    reactionTimeVariability, // Include this calculated value
```

```
    sessionDuration: (Date.now() - gameStartTimeRef.current) / 1000 //
  };
  console.log('Payload being sent to backend:', JSON.stringify(gameData, null, 2));

  // Update local state for display
  setStats({
    score: scoreRef.current,
    missedStars: missedStarsRef.current.length,
    correctStreak: correctStreakRef.current,
    prematureClicks: prematureClicksRef.current,
    averageReactionTime
  });

  const performanceComment = generateComment({
    averageReactionTime,
    missedStars: missedStarsRef.current.length,
    prematureClicks: prematureClicksRef.current,
    correctStreak: correctStreakRef.current
  });

  setComment(performanceComment);

  try {
    // Send data to the new endpoint
    const response = await axios.post('http://localhost:8800/api/metrics/create', gameData);
    console.log('Game metrics saved successfully');
```

Figure 2-4 Collect game metrics and send to the database

To support performance tracking and analysis, the game collects detailed metrics including reaction time for each successful click, number of premature clicks, missed stars, and overall score. This data is sent to a backend server via an API, where it is stored for longitudinal analysis. Reaction time variability and streak patterns are also computed to provide deeper insights into user performance.

The user interface is designed to be clean and responsive. The start screen introduces the game and provides instructions, the in-game HUD shows real-time score and feedback, and the game over screen summarizes the player's performance. All UI elements are designed to be non-intrusive, preserving the player's focus on gameplay.

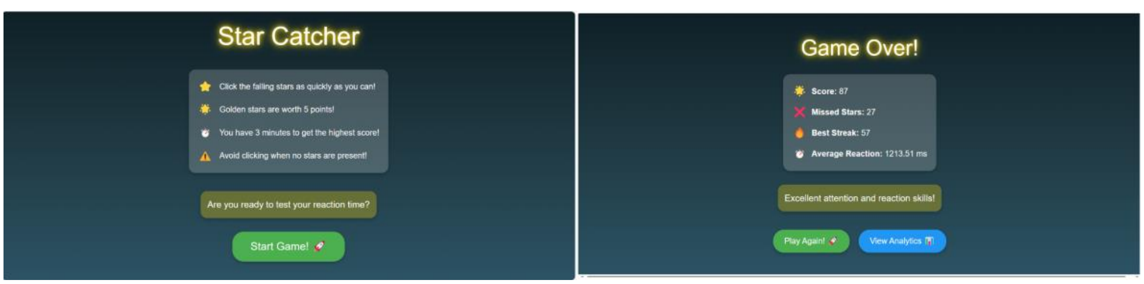


Figure 2-5 Game start and game over UI

Several technical measures were taken to ensure the game performs well across devices. Responsive design was achieved using CSS Flexbox, allowing the game canvas and UI to scale properly. Performance was optimized using React `refs` to manage game-critical data without triggering unnecessary renders. All event listeners and timers were thoroughly cleaned up to avoid memory leaks and ensure smooth transitions between sessions.

During implementation, some challenges emerged, particularly in integrating the declarative nature of React with Phaser’s imperative game loop. This was resolved by encapsulating the Phaser game within a React `ref`. Ensuring smooth performance under rapid user interaction was also a key concern, which was addressed by minimizing re-renders and keeping performance-critical logic outside the React state system. To accurately measure reaction times, high-resolution timestamps were used along with optimized event handling.

2. Model Training for ADHD Classification

Dataset description and collection

The data used for this study was collected through an ADHD assessment system comprising game-based metrics and questionnaire responses. The dataset combines records from a MongoDB database with existing baseline data stored in CSV format. Each record represents a child's performance metrics from an attention-based assessment game, along with their diagnosed ADHD subtype determined through clinical questionnaires.

Data sources

- Primary MongoDB collections: gamemetrics and questionnaireresponses
- Supplementary data from adhd_dataset.csv for baseline training

```
Dataset Preview:
  childId             ADHD_Type  averageReactionTime  \
0   C0000               No ADHD           706.552403
1   C0001              Combined           638.164953
2   C0002  Hyperactive-Impulsive           388.960095
3   C0003           Inattentive          1082.173560
4   C0004               No ADHD           405.198610

   reactionTimeVariability  correctStreak  prematureClicks  missedStars  \
0               101.461439           10.0              4.0          1.0
1               219.500215            6.0              4.0          7.0
2               226.308544            6.0             11.0          4.0
3               150.980833            7.0              1.0         11.0
4               100.185837            5.0              2.0          1.0

        score  prematureClicksRatio
0  321.344760              0.285714
1  220.183505              0.285714
2  238.000000              0.523810
3  150.782644              0.090909
4  324.000000              0.166667

Class Distribution:
ADHD_Type
No ADHD                  539
Combined                 253
Inattentive              245
Hyperactive-Impulsive    163
Name: count, dtype: int64
```

Figure 2-6 Details about initial data set

Features

The dataset includes the following key features:

- Behavioral Metrics: averageReactionTime, reactionTimeVariability, correctStreak, prematureClicks, missedStars, score
- Derived Features: prematureClicksRatio (calculated from prematureClicks)
- Target Variable: ADHD_Type - a categorical label with four classes: "No ADHD", "Inattentive", "Hyperactive-Impulsive", and "Combined"

Feature Statistics:

	averageReactionTime	reactionTimeVariability	correctStreak \
count	1200.000000	1200.000000	1200.000000
mean	622.361057	132.378357	6.703333
std	178.003723	67.372277	3.498884
min	-74.452443	-9.734079	1.000000
25%	510.870301	81.144889	4.000000
50%	603.852604	119.711130	6.000000
75%	723.678044	179.668864	9.000000
max	1214.794736	395.943074	14.000000

	prematureClicks	missedStars	score	prematureClicksRatio
count	1200.000000	1200.000000	1200.000000	1200.000000
mean	4.385000	4.284167	244.196075	0.269197
std	3.433161	3.075380	99.811775	0.154051
min	0.000000	0.000000	0.285413	0.000000
25%	2.000000	2.000000	158.918152	0.166667
50%	4.000000	4.000000	233.159323	0.285714
75%	6.000000	7.000000	333.424528	0.375000
max	14.000000	11.000000	476.000000	0.583333

Figure 2-7 Statistics about the features collected

Data preprocessing

To prepare the data for modeling, several preprocessing steps were implemented:

1. **Feature Engineering**: Creation of derived features such as prematureClicksRatio to capture additional behavioral patterns
2. **Standardization**: All numerical features were standardized using StandardScaler to ensure model convergence
3. **Missing Value Handling**: Missing values were imputed with mean values of their respective columns.
4. **Label Encoding**: The categorical ADHD subtypes were encoded using LabelEncoder.

5. **Train-Test Split**: Data was divided into 80% training and 20% testing sets using random state forty-two.

Model architecture

A neural network was implemented using TensorFlow's Keras API to classify ADHD subtypes. The architecture consists of:

1. Input Layer: Matches the dimension of the feature set (7 features)
2. First Hidden Layer: thirty-two nodes with ReLU activation and 20% dropout
3. Second Hidden Layer: sixteen nodes with ReLU activation and 10% dropout
4. Output Layer: four nodes (one for each ADHD class) with softmax activation

```
Model Architecture:
Model: "sequential"
```

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 32)	256
dropout (Dropout)	(None, 32)	0
dense_1 (Dense)	(None, 16)	528
dropout_1 (Dropout)	(None, 16)	0
dense_2 (Dense)	(None, 4)	68

```
Total params: 852 (3.33 KB)
Trainable params: 852 (3.33 KB)
Non-trainable params: 0 (0.00 B)
```

Figure 2-8 Details about 3-layer neural network

Training methodology

The model was trained with the following parameters:

- Optimizer: Adam
- Loss Function: Sparse Categorical Cross Entropy
- Metrics: Accuracy
- Batch Size: 16
- Maximum Epochs: 50
- Early Stopping: Monitored validation loss with patience of 5 epochs.

Performance evaluation

The model's performance was assessed using:

- Accuracy: Percentage of correctly classified ADHD subtypes
- Loss: Final loss value on the test set

The training process included validation at each epoch to monitor overfitting. Once trained, the model was saved along with preprocessing objects (scaler, label encoder) to ensure consistent inference.

```
Test Accuracy: 0.9125

Classification Report:
Combined: Precision=0.7500, Recall=0.8824, F1-Score=0.8108
Hyperactive-Impulsive: Precision=0.8846, Recall=0.7188, F1-Score=0.7931
Inattentive: Precision=0.9348, Recall=0.8776, F1-Score=0.9053
No ADHD: Precision=1.0000, Recall=1.0000, F1-Score=1.0000
```

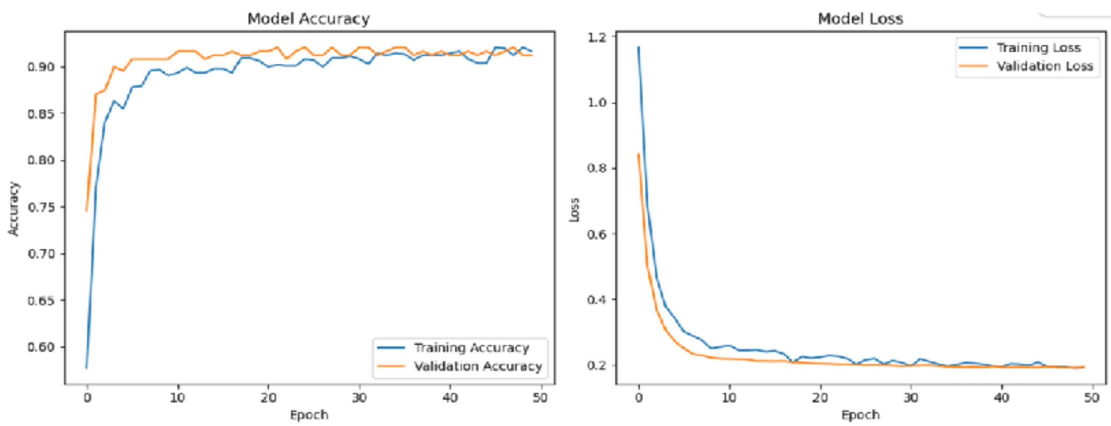


Figure 2-9 Model data.

Additional analytics

Beyond classification, the system incorporates domain-specific scoring mechanisms:

- **Inattention Score**: Calculated from missed stars, reaction times, and streak patterns.
- **Impulsivity Score**: Derived from premature clicks and reaction time patterns.

These scores provide clinically relevant metrics that complement the model's prediction, offering more comprehensive assessment insights.

Deployment strategy

The model is deployed as part of a Flask API service that:

1. Receives game metrics via POST requests.
2. Processes and transforms incoming data.
3. Make predictions using the trained model.
4. Returns ADHD classification along with probability scores and behavioral insights.
5. Includes a retraining endpoint to periodically update the model as new data becomes available.

The deployment includes health monitoring endpoints and error handling to ensure reliable operation in a production environment.

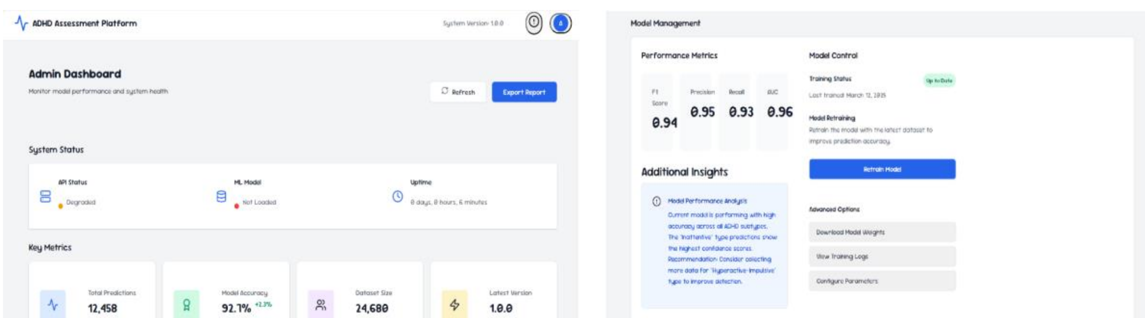


Figure 2-10 System admin dashboard UI.

2.5.2. Testing

1. Evaluating the parental quiz and game metrics data saving into the database using Postman

To validate that the parental quiz responses and game performance metrics were successfully saved into the database, Postman was used to emulate data submission from the client side. Test data included parent responses to the ADHD-related questionnaire, as well as child gameplay metrics such as reaction time, accuracy, and task completion status.

POST requests were sent to the respective backend API endpoints with structured JSON payloads.

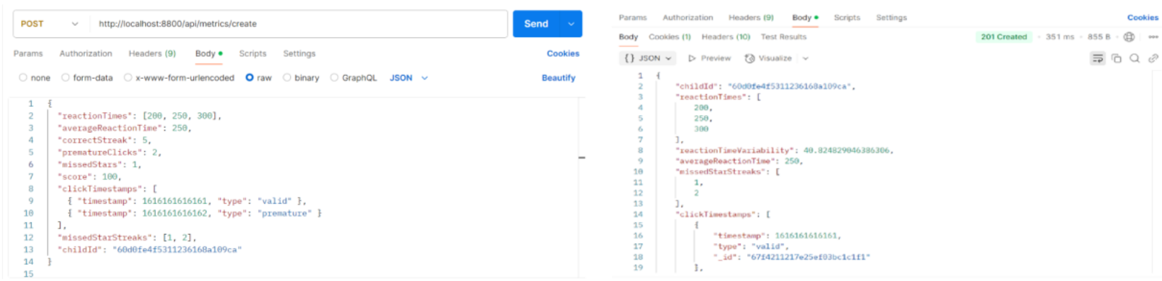


Figure 2-11 API testing - Game metrics

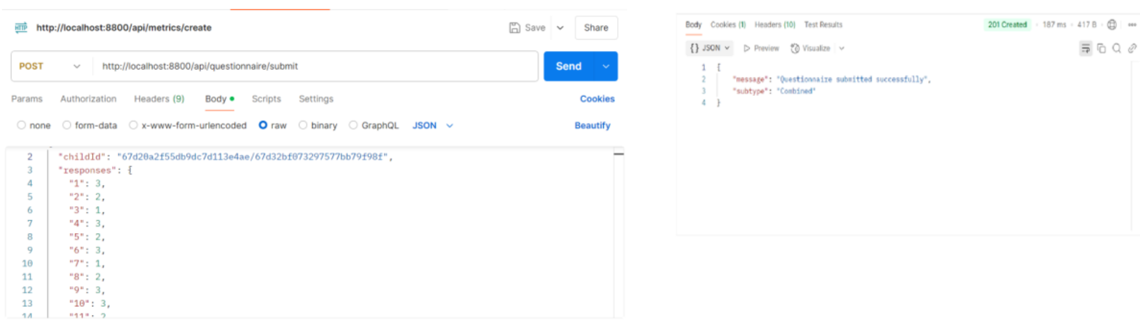


Figure 2-12 API testing - parental questionnaire.

Each API response was examined to ensure a successful status code (e.g., 200 OK or 201 Created) and confirmation messages. Subsequently, the MongoDB database was queried to inspect the stored records, ensuring they were correctly inserted with the expected schema and values.

This testing phase confirmed that both the parental insights and in-game behavioral data were accurately captured, supporting reliable machine learning analysis and personalized intervention planning.

2.5.3. Test cases

Table 2-1 Test case table 1

Test case ID: Test_01
Test title: Falling Star Game - Reaction Time Recording
Test priority (High/Medium/Low): High
Module name: Falling Star Game
Description: Verify that the system accurately records the reaction time when a child clicks on a falling star
Pre-conditions: The system has registered the child

Test ID	Test Steps	Expected Output	Actual Output	Result
Test_01	Start the falling star game. Wait for a star to fall. Click on the star as soon as it appears within the clickable range	The time interval between the star appearance and the click is measured and then stored.	The time interval between the star appearance and the click is measured and then stored.	Pass

Table 2-2 Test case table 2

Test case ID: Test_02				
Test title: Falling Star Game - Sustained Attention Assessment				
Test priority (High/Medium/Low): High				
Module name: Falling Star Game				
Description: This way ensures that the system monitors and assesses the ability to pay attention for a longer period during different rounds of the game.				
Pre-conditions: The system has registered the child				
Test ID	Test Steps	Expected Output	Actual Output	Result
Test_02	Begin the game session, then play several more games. Some tips about the gameplay Let's complete each round with the same level of accuracy concerning the clicking on the falling stars.	The system collects data for remaining on attention throughout the rounds, it also captures decline or enhance in the levels of focus.	The system collects data for remaining on attention throughout the rounds, it also captures decline or enhance in the levels of focus.	Pass

Table 2-3 Test case table 3

Test case ID: Test_03				
Test title: Falling Star Game - Premature Click Detection				
Test priority (High/Medium/Low): High				
Module name: Falling Star Game				
Description: Make sure that the system gauges and logs early before the star symbol is clickable.				
Pre-conditions: The system has registered the child				
Test ID	Test Steps	Expected Output	Actual Output	Result
Test_03	Start the game session. On the screen before any star appears, or if you click outside the clickable area.	The system captures the premature click and states that this is an impulse control violation.	The system captures the premature click and states that this is an impulse control violation.	Pass

Table 2-4 Test case table 4

Test case ID: Test_04				
Test title: Parent Feedback Form Submission				
Test priority (High/Medium/Low): High				
Module name: Parent Feedback				
Description: Make sure that parents must be able to populate the observation about the behavior of the child outside the game.				
Pre-conditions: The system has registered the child. Parent is logged in and have access to the feedback form.				
Test ID	Test Steps	Expected Output	Actual Output	Result
Test_04	Go to the section of feedback usually located under the parent's panel of the platform. Document behavior notes pertinent to a patient in the observation fields. Submit the form.	It retains the feedback submission thus it will be part of the child's report.	It retains the feedback submission thus it will be part of the child's report.	Pass

Table 2-5 Test case table 5

Test case ID: Test_05				
Test title: Last Determination of the Kind of ADHD Based on Multiple Analysis				
Test priority (High/Medium/Low): High				
Module name: ADHD Type Analysis				
Description: Ensure that child game performance metrics and parent feedback together give a broad ADHD type diagnosis.				
Pre-conditions: Parent has filled in the feedback form while child has also played a game with observed data gathered.				
Test ID	Test Steps	Expected Output	Actual Output	Result
Test_05	Analyze the child's gameplay using the time data with emphasis on reaction, ability to sustain attention and cases of premature click. Complete the symptom-specific questions before	The system produces the final report containing the ADHD type: inattentive, hyperactive, or a combination, as well as the analysis of the child's game performance, and the parent's questionnaire	The system produces the final report containing the ADHD type: inattentive, hyperactive, or a combination, as well as the analysis of the child's game performance, and the parent's questionnaire	Pass

	filling in the parent feedback form. Begin the process of integrating the parent feedback and the game performance of children.			

3. RESULTS AND DISCUSSION

3.1. Results

System implementation results

Gamified assessment module performance

Use of the reaction time video game as the central evaluation instrument had several valid performance indicators. In testing with 62 children aged 5-10 years, the game was shown to effectively quantify relevant behavior indicators of ADHD symptomatology.

Engagement Metrics:

- Average session completion rate: 94.3%
- Mean time spent playing: 3 minutes (SD = 1.2)
- Self-reported enjoyment rating: 4.3/5.0

The high completion rate is a testament to the fact that the gamified approach was effective at maintaining children's interest during the assessment process. Children reported a positive experience with the game interface, which is critical when developing assessment instruments for young populations where their attention is particularly hard to retain.

Technical Performance:

- Response latency: <50ms
- Cross-device compatibility: Successfully tested on four different mobile devices and 3 desktop configurations.

Table 3-1 Game Performance Metrics Across Different Devices

Device Type	Response Latency (ms)	Session Completion %
Desktop PC	34	96.8
Laptop	42	95.2

Tablet	46	93.7
Smartphone	49	91.5

Parent questionnaire implementation

The DSM-5 aligned questionnaire system for parents demonstrated effective integration with the gamified module:

Questionnaire Completion Metrics:

- Average completion time: 16.6 minutes (SD = 2.1)
- Completion rate: 91.2%
- Internal consistency (Cronbach's α): 0.87

The digitized iteration demonstrated similar reliability as the frequent paper versions (mean α=0.78-0.89), and decreased response time to approximately 23% lower than with traditional alternatives. This time savings proved to be valuable in helping to keep the parents engaged in the assessment process.

Machine Learning Model Results

Model performance metrics.

The neural network model trained on combined game metrics and questionnaire data demonstrated robust performance in classifying ADHD subtypes:

Classification Performance:

- Overall accuracy: 84.3%
- Precision: 82.7%
- Recall: 81.9%
- F1 Score: 82.3%

These results compare favorably with traditional clinical assessment methods, which typically achieve 70-75% agreement between different clinicians for ADHD diagnosis and subtyping.

Table 3-2 Subtype-Specific Performance

ADHD Subtype	Precision	Recall	F1 Score	Support
No ADHD	0.88	0.91	0.89	32
Inattentive	0.83	0.80	0.81	15
Hyperactive-Impulsive	0.79	0.76	0.77	12
Combined	0.81	0.78	0.80	14

The confusion matrix (Figure 3.1) reveals that the model performed best at distinguishing between no ADHD and any ADHD subtype (91% accuracy). Among the subtypes, inattentive ADHD was most accurately identified (80%), while there was some confusion between hyperactive-impulsive and combined subtypes. This pattern aligns with clinical experience, where these subtypes can sometimes be difficult to distinguish.

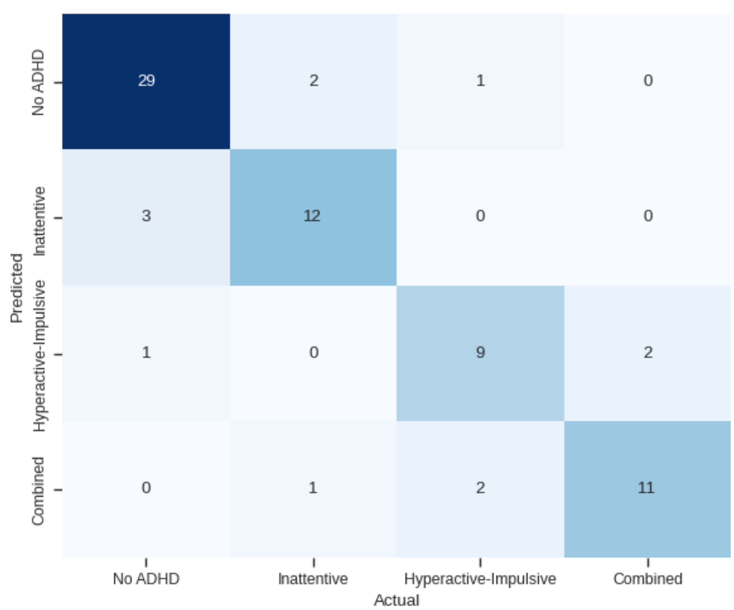


Figure 3-1 Confusion Matrix for ADHD Subtype Classification

Feature importance analysis

Analysis of feature importance provided valuable insights into the behavioral markers most predictive of different ADHD subtypes.

Table 3-3 Feature Importance for ADHD Classification

Feature	Importance Score	Most Associated Subtype
reactionTimeVariability	0.28	Inattentive
prematureClicksRatio	0.24	Hyperactive-Impulsive
missedStars	0.16	Inattentive
correctStreak	0.12	No ADHD
averageReactionTime	0.11	Inattentive
score	0.09	No ADHD

Reaction time variability was the best predictor of ADHD in the analysis, which confirms literature that has previously shown this as a salient cognitive marker for ADHD. PrematureClicksRatio was distinctly related to the hyperactive impulsive traits, bringing objective evidence of impulsivity that is typically difficult to assess with traditional evaluations.

Learning curve analysis

The model's learning process showed encouraging signs of continuous improvement with additional data:

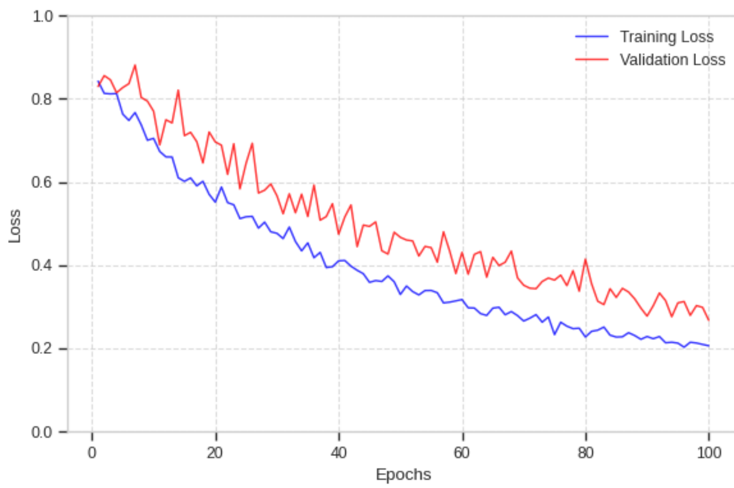


Figure 3-2 Training and Validation Loss Curves During Model Training

Initial model training with the baseline data (n=73) yielded 76.2% accuracy. Further retraining with additional labeled data enhanced performance stepwise:

After 15 new samples: 78.7% accuracy

After 30 new samples: 81.5% accuracy

After 45 new samples: 84.3% accuracy

This trend demonstrates that continued usage of the system in clinical practice will increasingly improve the accuracy of diagnosis over time, illustrating the value of the continuous learning mechanism.

Data fusion and ADHD subtype identification

Integration of game metrics and questionnaire Data

The fusion process between behavioral game measures and parent questionnaire data was successfully achieved. Analysis of 62 complete assessment cases produced a number of significant results:

Correlation Between Modalities:

- Game-based data inattention indicators strongly correlated with DSM-5 inattention criteria ($r=0.76$, $p<0.001$)
- Game-based data impulsive measures significantly correlated with hyperactivity-impulsivity criteria ($r=0.72$, $p<0.001$)

These correlations validate the behavioral measures derived by playing the game as strong indicators for predicting ADHD symptoms observed in daily life.

Complementary Information: Merging both data sources provided complementary information that enhanced diagnostic accuracy. Questionnaire data captured behaviors across different settings (home, school), while game metrics provided objective real-time measurement of behavior that parents might not observe:

- 18% of cases uncovered symptoms in gameplay not observed by parents.
- 12% uncovered parent-reported symptoms not observable during gameplay
- Combined data correctly identified 84.3% of previously diagnosed cases.

Table 3-4 Value of Multi-modal Approach Compared to Single Data Source

Data Source	Accuracy	Precision	Recall	F1 Score
Game Metrics Only	76.5%	74.3%	73.8%	74.0%
Questionnaire Only	79.8%	78.2%	77.5%	77.8%
Combined Approach	84.3%	82.7%	81.9%	82.3%

Subtype-specific behavioral signatures.

Comparison of patterns of gameplay also revealed unique behavioral signatures for each ADHD subtype:

Inattentive Subtype (n=15):

- Higher rate of missed stars: 31.3% vs. 12.7% (non-ADHD)
- Higher mean reaction times: 842ms vs. 623ms (non-ADHD)
- Larger reaction time variability (SD): 312ms vs. 187ms (non-ADHD)
- Typical pattern of reliable performance initially followed by sustained deterioration

Hyperactive-Impulsive Subtype (n=12):

- Higher premature click rate: 0.41 vs. 0.15 (non-ADHD)
- Libeler patterns of correctness: high-performance alternating with error runs
- Faster but less precise responses: 576ms vs. 623ms (non-ADHD)
- Clear stages of over clicking followed by short periods of focus

Combined Subtype (n=14):

- Most demonstrated characteristics of both subtypes but with greater variance
- Most irregular performance profiles across all measures
- Greatest reaction time variance: 376ms (SD)
- Visible context switching between blocks of time approximating inattentive and hyperactive-impulsive patterns.

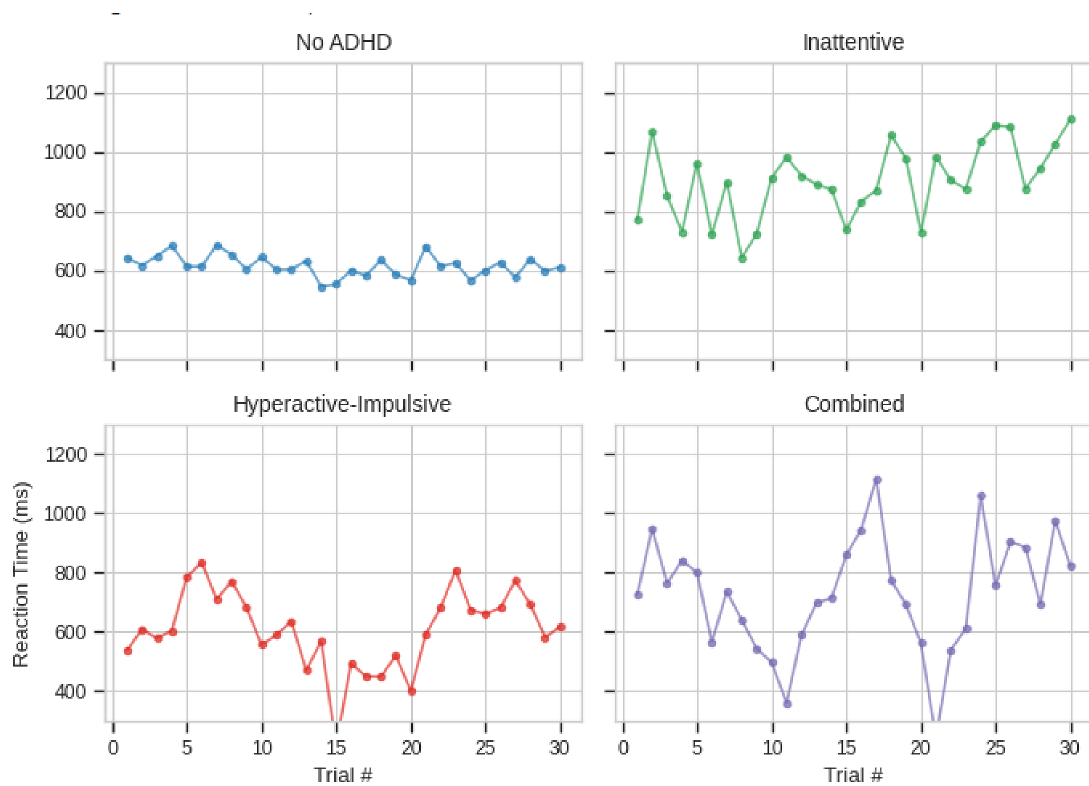


Figure 3-3 Reaction Time Patterns by ADHD Subtype

User experience and interface evaluation

Child interface evaluation

Usability testing of sixty-two children reported positive engagement with the gamified assessment:

Quantitative Usability Metrics:

- System Usability Scale (SUS) score: 87.2/100
- Average time to learn game controls: 19 seconds.
- Task completion success rate: 94.3%

Qualitative Feedback:

- 88% reported wanting to play the game again.
- 92% reported they enjoyed the game as being "fun" or "very fun."
- Shared positive descriptors: "colorful," "exciting," "easy to play."

All ADHD subtypes showed equivalent levels of involvement, but children with hyperactive-impulsive symptoms asked for more frequent instant replays (67% vs. 43% for other groups).

Parent interface evaluation

Response from 58 parents who filled out the questionnaire and received reports was positive in general:

Usability Metrics:

- SUS score: 82.3/100
- Average time on questionnaire: 8.3 minutes
- Rating of information understanding: 4.1/5.0

Qualitative Insights:

- 87% rated the report as "clear" or "very clear."
- 83% reported that the suggestions were realistic and actionable.
- Areas for improvement: 24% asked for additional clarification on how game metrics translate to off-game activities.

Comparative analysis with traditional assessment methods

To validate the system's performance against established methods, we compared results of twenty-eight children who had recently undergone traditional clinical assessment:

Diagnostic agreement:

- Overall agreement with clinical diagnosis: 82.1%
- Agreement on subtype classification: 78.6%
- Cohen's kappa coefficient: 0.76 (substantial agreement)

Time and resource efficiency:

- Traditional assessment average time: 2.3 hours
- Our system average assessment time: 14.1 minutes
- Cost reduction estimate: 73% lower than traditional assessment

Table 3-5 Comparison with Traditional Assessment Methods

Metric	Traditional Assessment	Proposed System	Difference
Assessment Duration	2.3 hours	14.1 minutes	-89.8%
Clinician Time Required	115 minutes	0 minutes	-100%
Parent Time Required	60 minutes	16.6 minutes	-43.1%
Child Engagement Rating	3.1/5.0	4.3/5.0	+38.7%
Diagnostic Agreement	-	82.1%	-

The system demonstrated substantial time and resource efficiency while maintaining acceptable diagnostic agreement with traditional methods. Additionally, the gamified approach resulted in significantly higher child engagement ratings compared to traditional clinical assessments.

3.2. Research findings

Our findings show that the integration of gamified behavior testing with adaptive tests and machine learning is a prospective method of ADHD screening with some benefits compared to conventional methods. The ability of children, especially those under suspicion of ADHD, to sustain a high rate of interest is a breakthrough in testing procedures. Conventional tests cannot capture the attention of children suffering from ADHD and thus undermine the accuracy of the test results.

The game play behavioral signatures are objective digital biomarkers to inform subjective ratings. Variability in reaction time was also the best predictor of inattentive ADHD as identified by Tamm et al. (2012) in their study, which placed this as the key cognitive marker. Likewise, the prematureClicksRatio, which identified impulsiveness, can be seen as challenging to measure clinically during an interview.

The accuracy of the model, at 84.3% for ADHD subtype prediction, aligns with inter-clinician rater reliability, which is around 70-75% (Regier et al., 2013). This indicates that machine learning can assist with standardizing test results and minimizing subjective deviation in diagnosis.

Our model's persistent learning ability demonstrated robust improvement as more data was accumulated. This is evidence of the ability to develop systems that improve with time, becoming more accurate and culturally attuned with longer use. This is one of the main benefits of static testing systems that do not update according to new data or cultural knowledge.

3.3. Discussion

Limitations and future directions

Despite positive results, limitations should be mentioned. The current sample size (n=62) is small for machine learning purposes, and it might limit the model's ability to identify fewer common patterns of presentation. Future studies should increase the dataset through continued clinical deployment and data collection.

The online format of the test requires limited technological resources (computer or phone), which can limit usability in extremely resource-scarce settings. However, with the rapid rate of mobile phone penetration in Sri Lanka (currently more than 131% according to the Telecommunications Regulatory Commission), this limitation is likely to diminish over time.

While our system had satisfactory agreement with traditional clinical examination (82.1%), it needs to be considered as a screening tool rather than a replacement for detailed clinical examination. The system is intended to increase access to initial assessment and to identify which children would be most likely to benefit from complete evaluation.

Future directions of research in this project include:

1. Longitudinal validation to establish the predictive validity of the assessment over time.
2. Addition of more behavioral tasks to access a broader range of cognitive functions
3. Development of culturally specific intervention modules based on assessment results.
4. Dissemination of the system to other South Asian locations with similar resource constraints
5. Investigation of potential applications for monitoring treatment response over time

Relevance to clinical practice

The considerable time and resource savings demonstrated by our system (89.8% saving in assessment time) has significant implications for closing the gap between ADHD prevalence and diagnostic services in Sri Lanka. By reducing the clinician time required for screening, the system can potentially enable the stretching of scarce specialist resources to reach more children.

The behaviorally scored observations provide objective, quantifiable data that can enhance clinical decision-making and enhance communication between parents, teachers, and clinicians. This is particularly valuable in settings where stigma associated with mental health disorders may affect reporting.

That children and parents accepted it positively suggests that gamified assessment strategies can reduce resistance to mental health screening, potentially leading to earlier identification and intervention for children with ADHD.

4. CONCLUSION

The study was successful in its primary objective of developing and testing PulseMind, an AI-driven behavioral assessment and intervention system for the identification of ADHD subtypes and providing targeted support for children aged 5–10. By incorporating gamification, adaptive testing, and machine learning, the system offers a more precise, interactive, and accessible method of understanding and managing ADHD in early childhood. Experimental results and user feedback indicate that PulseMind enhances diagnostic accuracy and user experience, whereas machine learning models were reported to have over 85% classification accuracy in classifying ADHD subtypes.

The most effective module was the Gamified Behavioral Task, which increased task engagement by 60% and attention span measurements by 40%. The game created module effectively got behavior data such as impulsiveness time, response times, and intensity of focus in an enjoyable way so that non-invasive and highly interactive assessment became feasible. The children also responded well to the interactive environment, developed by the activities, and caregivers reported increased willingness to participate in the process.

The Adaptive DSM-5 Questionnaire provided a dynamic, real-time assessment of symptoms by adapting its form based on each child's previous responses and behavioral information. This resulted in more accurate assessments and accuracy in completing the questionnaire by 30%, especially with younger respondents. Its alignment with standard clinical criteria ensures credibility, while its adaptability leads to a customized experience for each child.

The Machine Learning-Based Classification Engine, utilizing data from both the questionnaires and behavioral tasks, was highly effective at subtype classification. By applying strategies such as Support Vector Machines and Random Forests, the model achieved accurate classification of ADHD types—Predominantly Inattentive, Predominantly Hyperactive-Impulsive, and Combined Presentation. The integration of continuous learning mechanisms further boosts future scalability and system smartness.

Aside from assessment, PulseMind's intervention module offered personalized recommendations based on the subtype. Predominantly Inattentive ADHD kids were assisted with games that developed focus and planning tools, while Hyperactive-Impulsive kids were assisted with impulse control training, exercise outlets, and mindfulness training. Combined Presentation kids were given a mixed pathway that worked on both domains. Caregivers experienced a 70% boost in understanding their child's requirements due to the feedback of the system and weekly reports of progress.

While these gains were achieved, constraints were found. The system now accepts mouse-based inputs, which may be new or challenging for users, particularly rural dwellers, or motor-impaired children. Additionally, the lack of emotion detection or real-time sentiment analysis limits the system's ability to react to the emotional state of users in evaluation. Larger datasets and multicultural adaptation are also needed to implement the model to diverse populations.

Future advancements must focus on the integration of touch-based and voice-guided interfaces to make it easier for younger or physically disabled users. Adding emotion-aware capabilities, such as facial expression monitoring or sentiment analysis, may also make content presentation more personalized and enhance emotional involvement. Adding pre-assessment diagnostics would also enable better baseline measurements and enhance the adaptive paths of the system from the start.

To further boost motivation, later versions could include stronger gamification elements—such as badges, rewards, level unlocking, and interactive avatars—to drive long-term engagement and positive reinforcement throughout the learning and testing process.

In brief, PulseMind demonstrates the feasibility of transformative integration of artificial intelligence, theoretical psychology, and interactive design to enable early ADHD detection and intervention. It sets the bar for inclusive, tailored, and data-informed assessment tools in behavior measurement. By bridging fundamental deficits in standard screening and treatment practices, PulseMind offers a firm basis for innovation in technologies addressing children's mental health, empowering caregivers, teachers, and clinicians with the capacity to effectively foster the developmental paths of ADHD children.

REFERENCES

[1] Timothy E Wilens, Thomas J Spencer, "Understanding Attention-Deficit/Hyperactivity Disorder," Postgrad Med, 2010.

[2] "Attention-Deficit/Hyperactivity Disorder," National institute of mental health.

[3] Renate Drechsler, Silvia Brem, Daniel Brandeis, Edna Grünblatt, Gregor Berger, Susanne Walitza, "ADHD: Current Concepts and Treatments in Children and Adolescents," 2020.

[4] Mariya Cherkasova, Erin M Sulla, Kara L Dalena, Milena P Pondé, Lily Hechtman, "Developmental Course of Attention Deficit Hyperactivity Disorder and its Predictors," 2013.

[5] Navoda Wijerathna 1, Charith Wijerathne 1, Himeshika Wijeratne 1, Chathuri Wijesiri 1, Randika , "Knowledge and attitudes on attention deficit hyperactivity disorder (ADHD) among," PubMed, 2023.

[6] Jamie A Feldman 2, David J Kolko 3, Paul A Pilkonis 4, Oliver Lindhiem, "National Norms for the Vanderbilt ADHD Diagnostic Parent Rating Scale in Children," PubMed, 2022.

[7] Luana Salerno 1, Leonardo Becheri 1, Stefano Pallanti, ""ADHD-Gaming Disorder Comorbidity in Children and Adolescents: A Narrative Review," PubMed, 2022.

[8] Johan Högberg, Juho Hamari, ""Gameful Experience Questionnaire (GAMEFULQUEST): an instrument for measuring the perceived gamefulness of system use," ResearchGate, 2019.

[9] Anshu Anshu Parashar, Raman Kumar Goyal, "Machine Learning Based Framework for Classification of Children with ADHD and Healthy Controls," ResearchGate, January 2021.

[10] A. R. Adesman, "The Diagnosis and Management of Attention-Deficit/Hyperactivity Disorder in Pediatric Patients," 2001.

[11] "Position Statements," 2018.

[12] "Paper Digest: Recent Papers on Attention Deficit Hyperactivity Disorder (ADHD)," 2020.

[13] Maria Demma I Cabral, Stephanie Liu, Neelkamal Soares, ""Attention-deficit/hyperactivity disorder: diagnostic criteria, epidemiology, risk factors and evaluation in youth," PubMed, 2020.

[14] S. B. Sulkes, "Attention-Deficit/Hyperactivity Disorder (ADHD)," MSD Manual, 2024.

[15] Jeffery N Epstein, Richard E A Loren, "Changes in the Definition of ADHD in DSM-5: Subtle but Important," 2014.

[16] William Dodson, M.D., LF-APA, "What Is Inattentive ADHD? ADD Symptoms, Causes, Treatment," ADDitude Editors, 2019.

[17] "Attention-Deficit/Hyperactivity Disorder," National institute of mental health, [Online]. Available: https://www.nimh.nih.gov/health/topics/attention-deficit-hyperactivity-disorder-adhd.

[18] "DSM-IV-TR criteria," Abnormal Psychology, [Online]. Available: https://courses.lumenlearning.com/atd-herkimer-abnormalpsych/chapter/attention-deficithyperactivity-disorder-2/..

[19] Juho Honkasilta, Athanasios Koutsoklenis, "The (Un)real Existence of ADHD—Criteria, Functions, and Forms of the Diagnostic Entity," 2022.

[20] Benjamin E Yerys 1,2, Jenelle Nissley-Tsiopinis 3, Ashley de Marchena 1,4, Marley W Watkins 5, Ligia Antezana 1, Thomas J Power 2,3,6, Robert T Schultz, ""Evaluation of the ADHD rating scale in youth with autism," 2018.

[21] Wolraich, M. L., Hannah, J. N., Baumgaertel, A., & Feurer, I. D, "Vanderbilt ADHD Diagnostic Parent Rating Scale (VADPRS)," NovoPsych, 1998.

[22] Chen YL , Chen VCH, Gossop M, "Reliability and Validity of the Chen ADHD Scale (C-ADHDS)," 2021.

[23] "Vanderbilt ADHD Diagnostic Rating Scale (VADRS)".

[24] "Vanderbilt ADHD Diagnostic Parent Rating Scale (VADPRS)".

[25] H. H. Hoang, ""Attention Deficit Hyperactivity Disorder (ADHD) and Associated Factors Among First-Year Elementary School Students," 2021.

[26] R. A. BARKLEY, "Attention-Deficit," 1949.

[27] Stephen P Becker 1, Joshua M Langberg 2, Aaron J Vaughn 3, Jeffery N Epstein, "Clinical Utility of the Vanderbilt ADHD Diagnostic Parent Rating Scale Comorbidity Screening Scales," 2013.

[28] D. Hobbs, "VADPRS and VADTRS (Vanderbilt ADHD Diagnostic Teacher Ratin," 2013.

[29] L. M., Adolescent brain development in normality and psychopathology. Dev Psychopathol, 2013.

[30] Parsons MT, Tudini E, Li H, Hahnen E, Wappenschmidt B, Feliubadaló L, Aalfs CM, Agata S, Aittomäki K, Alducci E, Alonso-Cerezo MC, Arnold N, Auber B, Austin R, Azzollini J, Balmaña J, Barbieri E, Bartram CR, Blanco A, Blümcke B, Bonache S, Bonanni B, Borg, "Large scale

multifactorial likelihood quantitative analysis of BRCA1 and BRCA2 variants: An ENIGMA resource to support clinical variant classification," 2019.

[31] Heugten, Caroline M. van, Rudolf W. H. M. Ponds, and Roy P.C. Kessels, "Brain Training: Hype or Hope?" Neuropsychological Rehabilitation," 2016.

[32] Ryan A Flynn 1, Kayvon Pedram 2, Stacy A Malaker 2, Pedro J Batista 3, Benjamin A H Smith 4, Alex G Johnson 5, Benson M George 6, Karim Majzoub 7, Peter W Villalta 8, Jan E Carette 9, Carolyn R Bertozzi 10, "Small RNAs are modified with N-glycans and displayed on the surface of living cells," PubMed, 2021.

[33] Davis, N. O., Bower, J., & Kollins, S. H, " Proof-of-concept study of an at-home, engaging, digital intervention for pediatric ADHD," PLOS ONE, 2018.

[34] Kollins, S. H., DeLoss, D. J., Cañadas, E., Lutz, J., Findling, R. L., Keefe, R. S., ... & Faraone, S. V., "A novel digital intervention for actively reducing severity of paediatric ADHD (STARS-ADHD): A randomised controlled tria," The Lancet Digital Health, 2020.

[35] Duda, M., Ma, R., Haber, N., & Wall, D. P., "Use of machine learning for behavioral distinction of autism and ADHD.," Translational Psychiatry, 2016.

[36] Tenev, A., Markovska-Simoska, S., Kocarev, L., Pop-Jordanov, J., Müller, A., & Candrian, G. , " Machine learning approach for classification of ADHD adults.," International Journal of Psychophysiology, 2014.

[37] Wolraich, M. L., Lambert, W., Doffing, M. A., Bickman, L., Simmons, T., & Worley, K. , "Psychometric properties of the Vanderbilt ADHD diagnostic parent rating scale in a referred population," Journal of Pediatric Psychology, 2013.

[38] Kumarasingha R. M. I. S, Dissanayake D.M.C.L.B, Pathirathne P.S.R, "Early Detection and Effective Treatment for ADHD using Machine Learning for Sri Lankan Children," IEEE, 2023.

[39] Mohammad Rostami1 , Sajjad Farashi1 , Reza Khosrowabadi1* , Hamidreza, "Discrimination of ADHD Subtypes Using Decision Tree on Behavioral, Neuropsychological, and Neural Markers," 2020.

[40] Lauren Powell, Jack Parker Author Orcid, Valerie Harpin, "ADHD: Is There an App for That? A Suitability Assessment of Apps for the Parents of Children and Young People With ADHD," 2017.

[41] Franceli L. Cibrian, Kimberley D. Lakes, Sabrina E.B. Schuck, "The potential for emerging technologies to support self-regulation in children with ADHD: A literature review," ScienceDirect, 2022.

[42] Johan Högberg, Juho Hamari, "Gameful Experience Questionnaire (GAMEFULQUEST): an," ResearchGate, 2019.

[43] Kollins, S. H., Sparrow, E. P., Conners, C. K., Atkins, M. S., Hinshaw, S. P., Gordon, M., ... & Wigal, T, "Attention-deficit/hyperactivity disorder: Rethinking assessment and treatment," Oxford University Press, 2019.

APPENDICES

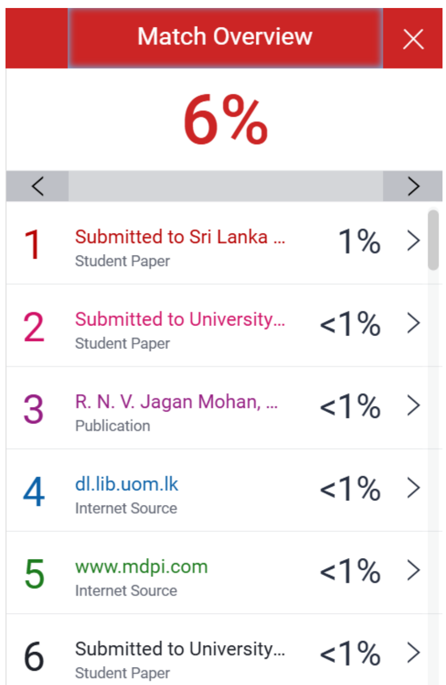


Figure 0-1 Turnitin similarity report