Towards a multimodal approach for assessing ADHD hyperactivity behaviors

Franceli L. Cibrian[1][0000-0002-7084-6904], Lauren Min[1], and Vitica Arnold[2]

[1] Fowler School of Engineering, Chapman University, Orange CA 92866, USA
{cibrian,laurenmin}@chapman.edu
[2] UC Irvine, Irvine, CA, USA
{vxarnold}@uci.edu

Abstract. Attention Deficit Hyperactivity Disorder (ADHD) is the most prevalent childhood psychiatric condition that needs an assessment of inattention, hyperactivity, and impulsiveness symptoms. Particularly in young children, hyperactivity-impulsivity stands out as a primary concern. However, those behaviors may or may not be evidenced when a child is in a small room, one-on-one with a single adult. Therefore, Ambient intelligence technology that supports data collection in a natural setting paired with expert human decision-making can potentially improve the quality of assessments. In this paper, we conduct a literature review and analysis to align ADHD assessment criteria with potential sensor technologies to collect behavior data, followed by design sessions proposing personas and scenarios to envision potential solutions.

Keywords: Multimodal · ADHD · Hyperactivity · Sensing

1 Introduction

Attention Deficit Hyperactivity Disorder (ADHD) is the most prevalent childhood psychiatric condition, affecting nearly 9.4% of children between age 2 to 17 in the United States (US) [22]. The assessment of ADHD involves a comprehensive evaluation of symptoms related to inattention (e.g., failing to pay close attention to details, maintaining attention on tasks, following through on instructions, and other related behavior) and hyperactivity and impulsiveness that includes two primary behavioral concerns: (1) movement (e.g., fidgeting, feeling restless) and (2) communication (e.g., talking too much or at an inappropriate time) [6]. Clinicians diagnose ADHD after analysis of behavioral observations and reports, sometimes combined with neuropsychological assessments and reports from caregivers and patients. Unfortunately, those reports can be influenced by factors intrinsic to the children themselves or extrinsic roles such as parents, the medical system, or school [34]. Therefore, the assessment can be biased, and many children and adults with ADHD go through years or even lifetimes without a formal diagnosis.

In young children, hyperactivity-impulsivity is the most predominant behavioral concern that eventually leads to an ADHD diagnosis [33]. Innovative computational approaches can support human experts in their diagnostic and assessment work by collecting data from sensors that support the decision-making of the experts and, in this manner, improve the accuracy of diagnosis and the acceptance by families and others of the clinical diagnosis procedure. For instance, literature has explored how to classify data collected from inertial or optical-based sensors (on the body, in the environment, or inherent to computational tool use) to sense the amount of activity or movements to identify hyperactivity behaviors related with movements (e.g., [44, 50, 38, 46, 49, 25, 55]).

However, situational appropriateness is a key variable to measuring hyperactivity [10]. For example, jumping or screaming must always be understood in the context of the activity (e.g., on the playground vs. in a quiet classroom). This context awareness remains an incredibly complex challenge (e.g., [24, 65, 1]). Therefore, we proposed to characterize the movements and communication skills in real scenarios instead of solely within lab studies. As a first step, we conduct a literature review and analysis to match the hyperactivity and impulsivity DSM-V Criteria with potential sensors that could give us accurate and contextual information on children's behaviors. We hypothesize that with these findings, we will develop a multimodal system to help us understand hyperactivity behaviors in a real scenario. The contributions of this paper are:

- An understanding of sensors that could be used to characterize hyperactivity and impulsivity behaviors in real context
- An architecture of a system that could help in the data collection of data related to hyperactivity and impulsivity behaviors
- A set of personas and scenarios to show the potential of the proposed technology.

2 Related Work

Research has focused mainly on assessing movement and gestures. Gesture analysis can be accomplished by examining interaction trajectories with tablets [46], Virtual Reality (VR) [25, 60], infrared motion tracking [44, 40, 41], and wearables [50, 38, 49, 55]. These studies show that measuring and predicting movement-related behaviors using data gathered from wearables is feasible and has increased understanding of the role of motor performance in ADHD individuals. However, the assessment of hyperactivity should require a multimodal approach by considering communication and socialization behavior as well.

A hybrid approach (wearable sensor, intelligent hardware, and mobile application) has been explored to support the assessment of ADHD. For example, Chen et al. [14] developed COSA, a contextualized and Objective System to support ADHD diagnosis. COSA assesses ADHD symptoms by gathering physiological, movement, and task-related data using three Serious Game formats. Clinicians, parents, and children found COSA acceptable in evaluative questionnaires, but no deployment study has been conducted yet. Similarly, the WEDA system, tested with 160 children ages 7 to 12, half with ADHD, attempted to discriminate between challenges in inattention from those related to hyperactivity and impulsivity, finding that the tasks cover all symptoms but perform better related to inattention [37], and has been tested with different approaches [45, 36]. Overall, these works show that it is possible to assess diverse ADHD behaviors using a multimodal technology approach. However, it is unclear how we can augment the current assessment tools to collect data augmented with context information.

3 Methods

We conducted a literature review and analysis to match the ADHD hyperactivity criteria from the DSM-V [6] with potential technology. Our methodology consisted of several interconnected steps: first, to determine which relevant literature we included in our review, we built upon a previous systematic literature review we conducted [17], using its findings to inform our initial selection of papers. Second, we supplemented this with a manual search focused on technology and sensors that could measure behaviors associated with the hyperactive subtype of ADHD, as defined by the DSM-5 criteria. As the DSM-V criteria are high-level descriptions of behaviors, we first analyzed three major ADHD assessments (from the Global North, English-speaking countries), Conners Scale [19], SWAN Ratings Scale [67, 66], BASC-3 Monitor Rating Scale [54]. Those assessments were supplemented with intersectionality ADHD literature to consider potential differences between gender, culture, race/ethnicity (e.g.,[9]). For each assessment, we analyzed items by item; in this manner, we could get a detailed description of behaviors. First, we split the items in those target hyperactivity/impulsivity behaviors from attention. Then, for those items, we then extracted the target behaviors. Lastly, We categorized and clustered the target behaviors to create a list of potential lower-level behaviors that could be measured with sensors.

We then conducted literature review for each target behavior related to digital health interventions, assessment, ADHD, Autism, and motion tracking (e.g., [69, 64, 63, 15, 16, 39]). For each paper, we analyzed the type of technology used, how they measure or characterize potential behaviors, and the experimental design conducted to collect data about the behavior. After that, we held design sessions to propose potential ideas for technological solutions that can collect objective data about the behaviors using affinity diagramming and brainstorming techniques within a Miro board [3]. To develop our user personas, we first identified key stakeholders in the diagnosis of ADHD in children based on existing literature [59]. Using an affinity diagram we mapped the stakeholders along the diagnostic pathway for ADHD. From this process, we identified two distinct diagnostic paths, which formed the basis for our two user personas, each representing a different scenario in the ADHD diagnostic journey.

[3] https://miro.com/

4 Results

Overall, this literature review shows that individuals with ADHD can wear sensors to collect behavioral data. This data can then be analyzed to uncover patterns that align with the hyperactivity and impulsivity criteria from DSM-V, which are measurable with technology.

4.1 Aligning technology with behaviors

According to the DSM-V criteria [6], experts need to assess nine main behaviors that are considered hyperactivity and/or impulsivity. Regarding physical movement, we found that hand/foot movements, physical activity, and movement transitions can be measured with inertial unit measurements embedded with wearables or motion-tracking cameras (Table 1). Many studies track physical activity using commercially available devices such as the Apple Watch (see Table 1 for reference examples). A particular example is when wearables measure the standing movement, which could serve from the criteria "Often leaves seat in situations." However, it lacks contextual information as the full criteria is "when remaining seated is expected." Similarly, physical activity, such as running, can be measured using smartwatches, but again, the context in which it occurs is crucial.

In terms of speech, we found that the analysis of speech and automatic discourse analysis could be helpful in finding differences. There is research detecting the percent of the time a person speaks during a conversation or detecting interruptions to detect conflicts (see Table 1 for reference examples). Still, it is unclear how this could be translated into the context of ADHD diagnosis. Moreover, privacy, confidentiality, and ethical questions arise as those are social behaviors that require the analysis of more than one person involved. As an alternative, we find that speech has been analyzed with voice-based interfaces varying in form factor (speaker such as voice assistant, assistive robots, virtual avatars) that could be used to mimic social situations to characterize the behaviors. However, the settings may be simulated, thus making it more difficult to mimic a naturalistic setting.

4.2 Design of HyperSense

After analyzing and matching behaviors with technological tools that could sense and collect data relevant to those, we brainstormed about a potential system that could support the data collection with proper contextual information to uncover hyperactivity behaviors in children. Therefore, we proposed HyperSense, a multimodal system incorporating sensors to collect multimodal contextual data about hyperactivity behaviors. The system will run on an iOS application for iPad and iPhone following the model-view-controller software design pattern. This model from the app will allow the connection via Bluetooth of a (1) Wearables: smartwatch, wearable motion sensors that will be worn for both wrist, ankles, and waist (this approach has been previously used to uncover stereotyped movements

Table 1. Aligment between ADHD Hyperactivity behaviors with potential technology to collect data

DSM-V Criteria	Measurable Behavior	Technology	References
1. Often fidgets with or taps hands or feet or squirms in seat.	Hand/Feet movements	Wearables with accelerometer, gyroscope	[53, 3, 32, 5, 42, 68]
2. Often leaves seat in situations when remaining seated is expected.	Stands up	Smartwatch (i.e., Apple Watch), Motion tracking camera	[61, 8, 57, 62]
3. Often runs about or climbs in situations where it is not appropriate (adolescents or adults may be limited to feeling restless).	Hand/Feet movements, Physical activity	Wearables with accelerometer, gyroscope, heart rate, physical activity, GPS	[29, 18, 30, 21]
4. Often unable to play or take part in leisure activities quietly.	Physical activity, Speak and noise levels	Microphone, GPS, wearables	[43, 11, 35, 27]
5. Is often "on the go" acting as if "driven by a motor."	Physical activity	Wearables with accelerometer, gyroscope, heart rate, physical activity	[20, 58]
6. Often talks excessively.	Speak	Microphone, recording, and speech analysis	[48, 52, 26]
7. Often blurts out an answer before a question has been completed.	Speak	Microphone, speech, and discourse analysis	[56, 12, 28]
8. Often has trouble waiting their turn.	Speak	Microphone, speech analysis	[2, 4, 23]
9. Often interrupts or intrudes on others (e.g., butts into conversations or games)	Speak	Microphone, discourse analysis	[13, 12, 28]

[3, 32, 5, 42, 68]; (2) a deep camera to track full body movements (this approach has been previously used to detect atypical movements [31, 51]; (3) Microphone, to record speech (to assess communication [47]). The view of HyperSense will allow specialists to label and score data to provide context information (Figure 1). We will also develop the controller to communicate the model with the view.

4.3 Personas and Scenarios

For the purpose of creating a realistic representation of those who will be utilizing HyperSense, we created two user personas to represent each user group. The personas were presented in user scenarios with two different outcomes, both utilizing HyperSense. The personas and scenarios are based on a hyperactive-inattentive ADHD student and a neurotypical student.

Scenario 1: Melanie (she/her) is a friendly and bubbly fourth-grade student who struggles with paying attention in class, often socializing during classwork and not listening to instructions. Her parents are struggling to get an ADHD diagnosis due to a disconnect between how they view her personality versus her teachers' observations of potential ADHD symptoms. Melanie's teachers notice her behaviors align with some peers with ADHD, so despite her parents attributing it to bad behavior, they enrolled Melanie's class in a HyperSense study by

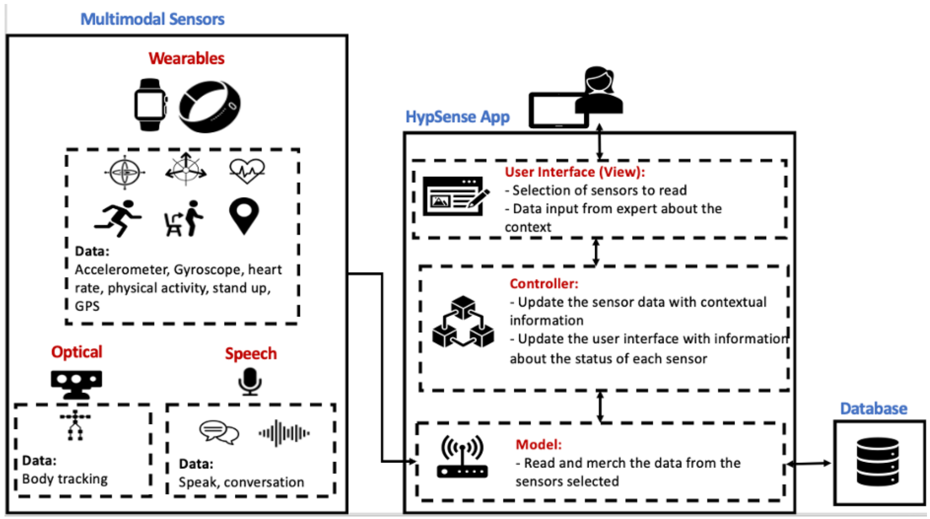

Fig. 1. A representation of HyperSense. From left to right: Potential sensors to assess behaviors such as wearables, optical, and microphones (left); the data gathered from the sensors will be labeled with contextual information using a mobile application developed following the model-view-controller software design pattern (center); the data from sensors augmented with contextual information will be stored in a file database.

an ADHD specialist. On the assessment day, students wear a smartwatch and sensors on their wrists, ankles, and chest that are connected to the app. The sensors discreetly record physiological responses, facial expressions, and interactions as they do activities to capture data on attention patterns, impulsivity, and other ADHD- related behaviors. The data shows while some students' behaviors are typical, Melanie displays ADHD symptoms like increased activity during lectures, verbal interactions during quiet work times, and restlessness. HyperSense results score Melanie with enough symptoms to suspect ADHD, and the specialist recommends further steps for a formal ADHD diagnosis and discusses potential interventions to support Melanie in both academic and social settings.

Scenario 2: James (he/him) is a 12-year-old student in San Jose, CA attending a competitive school district. When he is not busy studying for high school entrance exams, he spends time with friends. However, James struggles with time management skills, being punctual, and avoiding procrastination on schoolwork. He suspects he may have ADHD after being constantly told by his parents that he is too disorganized, which he has heard is a symptom. Recognizing James' challenges, his parents decide to seek a specialist's opinion and schedule a consultation with Dr. Revere, expressing concerns about his organizational skills, punctuality, and occasional difficulties with focus. Dr. Revere suggests utilizing the HyperSense system to score James' ADHD traits and see if a formal diagnosis is needed. As James engages in various activities, the app discreetly records his physiological responses, facial expressions, and verbal interactions.

After the assessment, Dr. Revere reviews the results, which surprisingly indicate James does not meet the criteria for an ADHD diagnosis based on attention and impulsivity traits. However, the results reveal elevated scores in some ADHD hyperactivity-related traits. Dr. Revere explains individuals can exhibit ADHD traits to varying degrees, and James may experience challenges related to hyperactivity, though not necessarily warranting a formal diagnosis. The specialist suggests strategies to address James' specific areas of concern. While not diagnosed with ADHD, James and his parents leave with valuable insights, helping James better understand his unique strengths and challenges.

5 Discussion and Conclusion

In this paper, we propose a novel multi-modal system, HyperSense, to track and store data on the behaviors exhibited by children seeking an ADHD diagnosis. Although this technology aims to improve the objectivity of ADHD diagnosis, we stress the importance of observing data collected from HyperSense in combination with context considerations. HyperSense aims to quantify those behaviors in the appropriate setting in order for stakeholders and healthcare professions to accurately diagnose patients. Additionally, we take into account the unique cognitive profiles of students with ADHD and the intersectionality those profiles might have given their identities.

Although children are asked for feedback in the ADHD diagnosis process, we found that parents or teachers act as key stakeholders, providing feedback that influences the assessments made by specialists. We also observed how the key stakeholders' subjective process for ADHD assessment creates a diagnosis gap for minority and marginalized populations. Therefore, we hypothesize that proper and fair technology design may help in the diagnosis process.

Unlike WeDA [37], COSA [14], and LemurDx [7], which were designed for clinical, classroom, and home settings respectively, our proposed system, HyperSense is designed specifically for the classroom enviroment. We recognize that teachers are often the first to identify atypical behaviors in students [59]. The classroom context provides a structured environment with behaviors expected of students, making it easier to recognize when ADHD symptoms arise. This targeted approach allows HyperSense to potentially detect ADHD behaviors more effectively in an educational setting.

We acknowledge that we need to actively involve experts and individuals with ADHD before proceeding with the development and evaluation of the system to properly provide design guidelines that support the fair development of the system aimed at characterized behaviors. Moreover, once the design of the application is evaluated and approved by experts and individuals with ADHD, we plan to conduct a deployment study with children with existing ADHD diagnoses and related hyperactivity behaviors and specialists in the care of ADHD. We will collect the data in a school-based context.

Overall, the findings of this paper are novel and could support other researchers in HCI and Ambient intelligent tecnology who are trying to characterize motion, taking into account the context.

This system will allow the development of novel machine learning approaches to characterize the hyperactivity of people with ADHD with the data collected from the proposed system and thus support the assessment and decision-making of ADHD diagnosis. This perspective has the potential to positively impact the entire life course of individuals with ADHD as well as their families.

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