Using a Webcam Based Eye-tracker to Understand Students' Thought Patterns and Reading Behaviors in Neurodivergent Classrooms

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ABSTRACT

Previous learning analytics efforts have attempted to leverage the link between students' gaze behaviors and learning experiences to build effective real-time interventions. Historically, however, these technologies have not been scalable due to the high cost of eye-tracking devices. Further, such efforts have been almost exclusively focused on neurotypical students, despite recent work that suggests a "one size fits many" approach can disadvantage neurodivergent students. Here we attempt to address these limitations by examining the validity and applicability of using scalable, webcam-based eye tracking as a basis for adaptively responding to neurodivergent students in an educational setting. Forty-three neurodivergent students read a text and answered questions about their in-situ thought patterns while a webcam-based eye tracker assessed their gaze locations. Results indicate that eye-tracking measures were sensitive to: 1) moments when students experienced difficulty disengaging from their own thoughts and 2) students' familiarity with the text. Our findings highlight the fact that a free, open-source, webcam-based eye-tracker can be used to assess differences in reading patterns and online thought patterns. We discuss the implications and possible applications of these results, including the idea that webcam-based eye tracking may be a viable solution for designing real-time interventions for neurodivergent student populations.

CCS CONCEPTS

• **Applied computing** → Education; Computer-assisted instruction; Interactive learning environments; • **Social and professional topics** → User characteristics; • **Human-centered computing**;

KEYWORDS

Educational technology, Neurodivergence, Eye-Tracking, Webcam-based tracking

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1 INTRODUCTION

The ultimate goal for adaptive educational technologies is to improve students' educational experiences by providing an experience that responds to their needs, much like a classroom teacher or a tutor might. Such technologies often attempt to capture information that characterizes some aspect of the learner's experience (e.g., knowledge of a concept, engagement, etc.; [2, 6, 27]). This information is then utilized to build algorithms that inform real-time interventions during learning [15]. For example, these systems include hypermedia learning systems and intelligent tutoring systems–both of which provide instruction tailored to an individual student and have risen in popularity as a result of increased internet access and the COVID-19 pandemic (e.g., [34]). A key aim of these adaptive technologies is to help *all* students, though less work has ensured such benefits are realized by neurodivergent students [8, 35].

The current research attempts to address this gap by exploring a novel way to support neurodivergent students through unobtrusively monitoring their gaze while learning from an online reading platform. The basic idea is as follows: based on prior research, neurodivergent students may benefit from supports that are tailored to their individual experiences (i.e., their familiarity with the material) and thought patterns (i.e., their level of mind wandering or "sticky" thought) [20, 37]. Here we test whether eye-gaze may be one possible marker of such patterns. Indeed, there is ample reason to believe that eye-gaze is a reliable marker of online thought patterns and reading behaviors [39, 50, 52]; however, past solutions, which employ eye-trackers that cost anywhere from hundreds of dollars to twenty-thousand dollars, are simply not a viable solution for helping students based on cost alone—neurodivergent or not. We thus explore a highly scalable solution, which uses a free, open-source, webcam-based eye-tracker that requires nothing other than access to a stock webcam, an item that is now almost ubiquitously available on personal computers. Further, our solution considers students' privacy as it does not store or record any images or videos of students.

1.1 Theoretical Background and a Call for Attention to Neurodivergence

The term "neurodivergent" can be defined as having a brain "different" from the norm and has become an umbrella term in education for students with diagnoses of autism, ADHD, a learning disability (LD), or a psychiatric condition, among others. The use of this umbrella term acknowledges that brain-based differences exist in learning, cognition, attention, mood, and personality—among other neurocognitive functions. It further assumes these variations result from normal, natural variation in human evolution. This framework is thus meant to broaden perspectives on what is "normal," and to encourage greater empathy, understanding, and accommodation of these differences.

In the current research, we chose to examine a relatively broad range and definition of neurodivergence by focusing on students with any combination of ADHD, LD, and/or autism diagnoses, rather than attempt to sample particular diagnoses, given the shared characteristics across these profiles. This is evidenced by the high degree of co-occurrence, or co-morbidity, across diagnoses for individuals with ADHD, autism, and LD. For example, for a child with autism, the co-occurrence of meeting the diagnostic criteria for ADHD (or vice-versa) is high, with estimates ranging from 20-80% [64]. Similarly, the co-occurrence of a learning disability and ADHD are estimated to have a 31% to 45% overlap [28]. Common genetic markers have also been observed across these diagnoses [33, 46, 62]. In short, individuals having a single diagnosis of LD, ADHD, or autism are common, but nearly as common are individuals having co-morbid diagnoses, which is partially explained by sharing common genetic characteristics.

While diagnoses are useful, in our work with neurodivergent college students, we find that examining functional challenges, regardless of specific diagnoses, can be informative in ecologically meaningful academic settings. Shared cognitive and learning challenges are common across these three profiles; in particular, executive function difficulties are prevalent among individuals with each of these diagnoses [7, 9, 22, 47]. Executive function (EF) is an umbrella term that refers to the neurocognitive processes involved in executing goal-directed behavior [76]. This focus on functional challenges, rather than diagnoses, is supported by others in the field [23, 58]. Thus, in keeping with the goal of assessing eye-tracking as a reliable way to track student reading behaviors—namely, their familiarity with the text and their thought patterns during reading—in neurodivergent students within real-world settings, we intentionally recruited students with and without multiple diagnoses.

We argue this work is particularly timely given the uptick in neurodivergent diagnoses combined with the increased awareness of such diagnoses in recent years [21, 48], despite less work devoted to these students within the learning analytics space. Though there are some exceptions in adjacent fields, such Human-Computer Interaction (e.g., [69]) and Educational Data Mining [54], we could not find evidence that papers published in the Learning Analytics and Knowledge Conference (LAK) have historically considered for the needs of neurodivergent student populations. Specifically, we searched the LAK proceedings in ACM's digital library for the following terms: neurodivergence, neurodivergent, ADHD, autism, ASD, and learning disability. Zero results were returned. We argue that the work presented here represents an important piece of what the field of Learning Analytics has to offer *all* students, especially as we attempt to build a more inclusive society.

1.2 Related Work

1.2.1 Designing for Neurodivergent Students.

Neurodivergent students tend to display atypical behaviors during learning, which are frequently related to their learning differences [12, 31]. However, these behaviors are rarely taken into explicit consideration in developing adaptive technologies, which are developed primarily with neurotypical students. As a result, some adaptive educational technologies may fail in helping neurodivergent students. Some of these limitations may be addressed by considering the documented differences in educational settings that present challenges to neurodivergent students [29].

For example, neurodivergent students tend to display atypical reading behaviors, which are thought to underly lower reading comprehension performance [49, 59]. These differences in behavior have been shown to exist as early as elementary school, resulting in differences in learning gains that persist throughout the students' academic careers [30]. Given these differences in reading behaviors, the current study focused on determining if a scalable eye-tracking solution may be useful for tracking important aspects of reading that can be used to inform future real-time interventions for neurodivergent students specifically.

One marked difference between neurotypical and neurodiverse individuals is their ongoing thought patterns, such as their levels of task-unrelated thought (TUT; commonly referred to as *mind wandering*; [53]), which is when thoughts shift away from the current activity to some internal stream of thought. Previous research suggests that neurodivergent students experience TUT more often than neurotypical students [32, 56, 67]. On one hand, the ability to escape the external world through TUT is likely beneficial, especially for creative thinking and future planning [5, 55]. On the other hand, mounting evidence points to consistent performance decrements when students experience TUT during learning [11, 26, 72]. This is likely because TUT can lead to a state of 'perceptual decoupling' from the external environment, in which there is reduced processing of auditory and visual information [42].

Despite the utility of tracking TUT in educational settings, there is reason to believe that other thought dimensions related to mind wandering may also be relevant—particularly in the context of designing for neurodivergent students [3]. This is partly based on recent work speculating that TUT may be a rather simplistic content-based dimension of thought (on vs. off task), which does not fully capture the dynamic complexity of how thoughts arise and unfold over time [18, 19, 53]. One dimension that may be particularly relevant to the current work is when thoughts are "automatically constrained," such that the internal stream of thought is non-deliberately captured by affective, habitual, or sensory salient stimuli [19]. As an example, consider times when you may have found yourself "stuck" in your own thoughts; you may have felt it *difficult* to *disengage from your thoughts* when you were trying to solve a problem, when you were worried about something, or when you felt compelled by a daily habitual practice.

Indeed, such difficulty disengaging is quite common for neurodivergent students. They often report having difficulty disengaging [65] and increased fixatedness [13] and may represent a helpful opportunity for supportive in-the-moment interventions during learning. For example, given well-known links to EF differences, neurodiverse students may benefit from embedded supports that can help regulate where attention is directed, especially when it may become fixated. Such supports can be thought to support the EF challenges that are observed in many, although not all, neurodivergent individuals [4, 14, 25, 47]. However, to our knowledge, there are no studies investigating how to track such in-situ thought patterns *during* ecological learning experiences, and it is further unclear if a scalable eye-tracker could be helpful for identifying such instances when students feel "stuck" in their thoughts.

1.2.2 Eye-tracking as a Measure of Online Processing. Eye trackers record gaze locations which can be used to determine saccades (periods of movement) and fixations (periods without movement). Research has shown links between eye gaze and ongoing thought patterns—often referred to as the "eye-mind link" [60, 61]. It is generally assumed that attention is focused on where the eyes are fixated (e.g., [36, 75]). Eye gaze provides a real-time index of the information-processing priorities of the visual system because physiological and cognitive limitations on vision, attention, and memory require the eyes to shift from location to location to construct a comprehensive representation of the external world. Therefore, eye movements provide a reflection of where a person's visual attention is allocated.

Using eye trackers within interactive technologies is not a new idea—though their cost is likely prohibitive for making this technology commonplace in educational technologies. Recent work has considered eye tracking as both a primary interaction method [41, 43] as well as an augment to the 'classic' interaction methods [70]. One example of eye tracking within learning technology includes GazeTutor [27], which built upon the AutoTutor framework and used eye gaze to monitor attention. If a student was perceived to be disengaged, the tutor would stop what it was saying to deliver a short phrase designed to redirect the student's attention, such as *"Please pay attention,"* or "*I'm over here, you know."* Here, a student who was not looking at the screen for five seconds was assumed to be disengaged. This assumption, though successful, did not consider the nuances of gaze behaviors; for example, a student could be closing their eyes to concentrate. Mills et al. [52] leveraged more detailed eye tracking in a learning technology that detected TUT as students read an educational text. The detection of TUT was then used to drive interventions designed to reengage students and correct any knowledge deficit resulting from the TUT. Though conducted in the lab, Hutt et al. [38] used a similar approach to respond to TUT in an intelligent tutoring system designed for classroom use. The system was evaluated in the classroom with students interacting simultaneously in a class, demonstrating the potential for bringing eye tracking into the environments where learning was happening, rather than the reverse.

Critically, the research reviewed above relied on research-grade eye trackers, which are expensive (~30,000 USD) and not readily available outside of laboratories (with the exception of [38] that used a commercial off-the-shelf eye tracker, but which still retails for $100 USD). As a result, webcam-based eye tracking has emerged as an alternative and is growing in popularity; it allows any user to be at their computer using their own webcam and thus offers the first scalable solutions for eye-tracking in terms of cost and accessibility. Prior research has validated the use of webcam-based eye trackers through comparisons with commercial eye trackers; however, one limitation of webcam-based eye trackers is that they can be less accurate and precise [71, 74]. Given that prior research has used eye tracking to study in-situ thought patterns, we test if this assumption holds for neurodivergent students in ecological classrooms. Specifically, we assess whether eye-gaze is reliably related to ongoing thought patterns related to mind wandering. This question is important to address when considering the potential scalability and utility of webcam-based eye trackers that were originally developed predominantly with neurotypical users. Although there is already compelling evidence that eye tracking technology can be used to track reading patterns in neurodivergent populations [16, 24, 63], these were using commercial-grade eye-trackers—making generalizability a central issue that to address.

Finally, in addition to in-situ thought patterns, the webcam-based technology should also demonstrate that it is sensitive to basic features of reading behaviors that are related to the ongoing comprehension process of the reader. Here we focus on students' familiarity with the text based on whether they have read the text before. Prior research suggests that reading behaviors differ based on if the text has been read before [40, 66]. When reading texts multiple times, reading times are faster and readers are less likely to make regressions (backward saccades) during subsequent readings than the initial reading [40]. Related to the challenges mentioned above regarding EF, supporting students based on their prior exposure to a text may be a helpful real-time support, particularly for students that have challenges allocating their attentional resources and planning.

1.3 Overview of current study

The present study aims to examine if webcam-based eye tracking can be reliably used to track thought patterns and reading behaviors of neurodivergent students in an ecological setting. Students at an institution serving only neurodiverse students read texts on their personal computers during a typical class meeting. They answered periodic "thought probes" about their ongoing thought patterns while gaze measures were recorded by a webcam-based eye tracker. The study had three questions of interest:

1. Is a webcam-based eye tracker deployed in an ecological classroom with little-to-no researcher presence capable of returning valid and reliable data from a neurodivergent population?
2. Are gaze behaviors (gaze location, off-screen behavior, etc.) measured with a webcam related to students' in-situ thoughts, and how much gaze data is needed to detect this relationship?
3. Are eye-gaze behaviors sensitive to text familiarity (i.e., whether the text has been read before)?

To our knowledge, this is the first eye gaze data collection of this size (N = 43) in an ecologically valid environment with neurodiverse students. Secondly, this study represents the first attempt

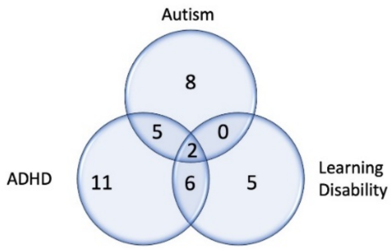

Figure 1: Co-morbid diagnosis of LD, ADHD, and autism in the experiment sample

to evaluate the possibility of using webcam-based eye tracking as a way to support neurodiverse students during learning.

2 METHODS

2.1 Participants

43 participants (28 Male, 11 Female, 2 Non-binary, and 2 Prefer not to say) were recruited from three classes of an Education course at Landmark College. The sample had a mean age of 20.28 (SD = 2.22). Landmark College is one of only two post-secondary institutes that exclusively serve neurodivergent students (defined here as having a diagnosis of ADHD, autism, and/or learning disability). Landmark College provides integrated teaching methods for neurodivergent college students via a strengths-based approach, following principles of Universal Design for Learning to provide accessible curricula, engage students via multiple means, and allow for flexible assessment, when appropriate. Executive function and classroom strategies are fostered to develop student self-determination and self-efficacy. Figure 1 displays the cross-tabulation of the diagnostic categories of interest in the current study.

2.2 Design

Participants were recruited from a required first-year seminar in coordination with their instructors and research personnel. This course introduces cognitive, social, emotional, and cultural theories of learning and focuses on fostering student self-awareness, strategic learning, and self-advocacy. Students reflect on learning and teaching processes while applying, practicing, and transferring learning strategies to other courses. Any student enrolled in this course during the Spring 2022 semester was both eligible and asked to participate in the study. Educational material used in the study was tailored to existing class content, namely, a required reading for all students enrolled in the course (more on the article below in Materials).

In order to test if the webcam-based eye-tracker is sensitive to reading behaviors associated with familiarity, we adopted a between-subjects, quasi-experimental design with two "reading" conditions: *never read* vs. *previously read*, as determined by individual sections of the course. For the *previously read* condition, students already read the article at the beginning of the semester, and thus had prior familiarity with the text at the time of the study. The students in the *never read* condition saw the text for the first time during the study and thus had no prior exposure.

2.3 Materials and Methods

The text consisted of an excerpt from "The Power of Habit" by Charles Du Higg. The text is an assigned reading in the first-year seminar from which participants were recruited. This text examines habit formation, including recognizing the antecedent cues and subsequent rewards that help form and shape most habits. It sets the stage for discussing routines and forming beneficial habits, as well as breaking undesirable habits. The connection to positive habit formation as a correlate to academic success is discussed in length in this course. The excerpt was divided into 40 paragraphs following the divisions of the original text. Paragraphs contained an average of 2.8 sentences and 46 words.

Gaze locations were collected using Webgazer [57]. Webgazer is a Javascript library that infers gaze locations using the user's webcam. Webgazer can be implemented with any website as long as access to the user's webcam is provided. In order to make its predictions, Webgazer first uses facial and eye detection algorithms to determine pupil location and represent the eye as an image patch. It then uses a ridge-regression model to map pupil locations and eye features to gaze locations. Webgazer uses a temporal interval of 500ms when determining x- and y-coordinates. Webgazer has been shown to achieve a 4.17° gaze accuracy [57] compared to the <1° gaze accuracy achieved by commercial-grade eye trackers. Despite the lower accuracy, several studies have used Webgazer to replicate findings from studies that used commercial-grade eye trackers [68, 71, 74]. Though Webgazer uses webcam images in its algorithms, it does not record any webcam video. WebGazer's output consists of x- and y-coordinates of where Webgazer calculates the user is looking at a given time.

Two probe questions were used to assess the online thought dimensions of TUT and difficulty disengaging (see Figure 2). For task-unrelated thought, participants were asked, "Immediately before this question popped up, were you thinking about anything other than the task right now?" For difficulty disengaging, participants were asked, "Immediately before this question popped up, do you feel like it would be difficult to disengage from your thoughts?" For both questions, participants answered either yes or no. These questions have been used in prior research and responses have been found to correlate with mental health disorders [3] suggesting psychometric properties of validity.

2.4 Procedure

Participants completed the experiment using the Google Chrome browser on laptops in one of three classrooms. Two of the rooms had half artificial light and half natural light, and the third used primarily artificial light (see Figure 3). Critically, there was minimal experimenter presence and we offered no support in terms of the eye-tracking by design in order to determine the feasibility of this approach in terms of usability.

Participants first completed Webgazer's initial calibration in which participants followed a dot with their eyes as it moved across the screen to 13 locations. Participants were then informed that they would be reading a text and would be answering questions about their thoughts.

Next, participants completed a pseudocalibration which consisted of looking at a dot in 5 different positions on the screen. This

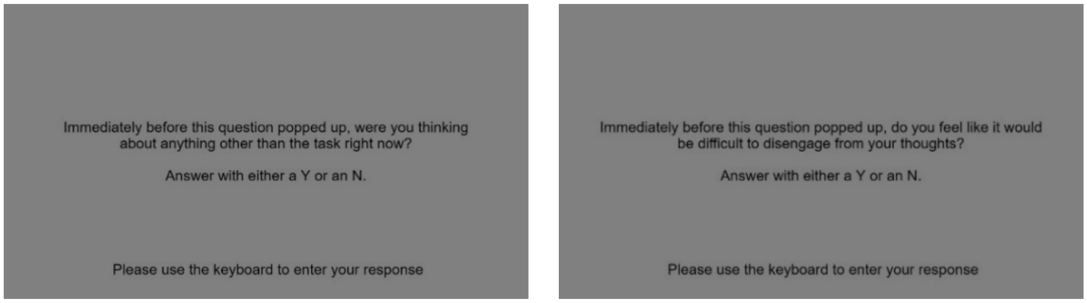

Figure 2: Display of probe questions for task-unrelated thought and difficulty disengaging

Figure 3: Classroom locations

procedure was to check if the initial calibration had changed. Participants read the text self-paced and were presented one paragraph at a time.

Participants were asked to answer a "thought probe" periodically, in which probes were interspersed throughout the reading to get a "mental snapshot" of their ongoing though patterns with minimal interruptions. This method is the gold standard for assessing mind wandering, and it is the most common measure from prior research examining TUT during reading [51, 72]. Participants were probed after the 4^{th}, 10^{th}, 15^{th}, 20^{th}, 26^{th}, 30^{th}, and 36^{th} paragraphs for a total of 7 probes. During the reading and probe phase, participants' gaze behavior was recorded using the webcam-based eye tracker. After reading the text, participants were asked if they had read the text before and then answered demographic questions and self-reported any diagnoses of neurodivergence. Of the 43 participants, 25 had not previously read the text, and 18 had previously read it as part of their class assignments. The experiment lasted approximately 40 minutes.

2.5 Gaze processing

Three gaze measures were calculated for each paragraph using the gaze locations reported by Webgazer. Number of gazes was calculated as the total number of gaze locations. Area of interest (AOI) gazes was the number of gazes within an AOI. For each paragraph, the AOI was defined as the paragraph text. Offscreen gazes was the number of gazes that were not on the screen. Prior research has shown that these gaze measures are predictive of TUT [27, 39, 52]. AOI gazes provides a measure of attention and offscreen gazes provides a measure of disengagement. Because number of gazes is directly correlated with reading time, AOI proportion and offscreen proportion were calculated by dividing the relevant measure by the total gazes for that paragraph.

AOI and offscreen proportions were calculated for each paragraph read (i.e., one screen at a time). Thus, there is a question of how many paragraphs preceding the thought probes would be needed to observe any relationship between thought probes and gaze behaviors (i.e., how much data is needed?). We therefore analyzed different time windows (akin to approaches used by [10, 50]) each with gaze measures being aggregated across different window sizes, where window size refers to how many paragraphs were included. We included four different windows, ranging from one (i.e., only 1) to four (i.e., 1-4) paragraphs preceding the thought probe (e.g., gaze from 1 preceding paragraph only, gaze from 2 preceding paragraphs aggregated, etc.).

3 RESULTS

Table 1 presents the demographic distribution of participants by condition. We present the results of our study through three sets of analyses. We begin with a qualitative inspection of the data, providing initial validation that the data collected through the webcam was reasonable and sufficient for further analysis. We then examine the relationships between gaze behavior (as recorded by WebGazer) and in-situ thoughts. Finally, we consider the moderating effect that previous reading of the text may have on gaze behaviors.

3.1 Qualitative inspection

Because of the relative novelty of this gaze-tracking approach, it was not initially clear if this method would yield valid gaze data when collected in the classroom. This is particularly true when considering the number of external challenges that ecologically

Table 1: Demographic Distribution by Condition

	Never Read	Previously Read
Age (M(SD))	20.4 (2.38)	20.1 (2.02)
Gender		
Male	17	11
Female	6	5
Other/Non-Binary	1	1
Prefer not to say	1	1
Diagnosis[a]		
ADD or ADHD	14	10
Autism, Asperger's, or ASD	6	9
A specific learning disability (such as dyslexia)	9	0
Any other language, reading, math, and nonverbal learning disorder	2	4
Generalized anxiety disorder	2	4
Other	7	1

[a] Participants were allowed to report more than one diagnosis

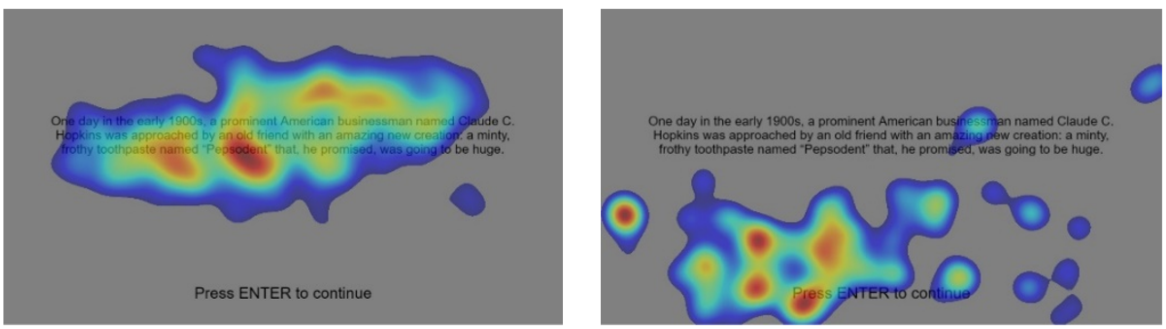

Figure 4: Example heatmaps of gaze locations

valid environments can bring. As such, to determine if the webcam-based eye tracker was capable of returning valid and reliable data (research question 1), we conducted a qualitative analysis by simply visually inspecting the gaze. That is, does the data indicate that people were looking where we might generally expect them to look? Figure 4 shows the heatmap of gaze locations for an example paragraph of two participants. From inspection, it appears that a webcam-based eye tracker has the capability to track reading behavior of a neurodivergent population, as evidenced on the left. However, the limitation of using visual inspection is there are instances of atypical gaze locations (as shown on the right in Figure 4) that could not be differentiated between atypical reading behavior or poor calibration. Comparisons between lighting conditions in the rooms were not performed due to a confound as the participants that performed the experiment in the room with mostly artificial lighting were comprised mainly of the previously read condition.

3.2 Gaze behaviors and in-situ thoughts

The next set of analyses examined what gaze behaviors were related to in-situ thoughts (research question 2): task-unrelated thought and difficulty disengaging. Analyses were performed by regressing probe responses on proportion of time spent in AOI and offscreen gazes. The count of gazes was not used in these analyses because it would be confounded with paragraph length. Specifically, we used generalized linear mixed effects models with probe responses as the dependent measure and the gaze measures as continuous fixed effects. Random intercepts for participant and probe number were included. Table 2 shows the relationships between the gaze measures and probe measures by number of preceding paragraphs. Offscreen gaze proportion was not significantly related to TUT or difficulty disengaging, regardless of how much data was used preceding the thought probe. AOI gaze proportion was also not significantly related to task-unrelated thought.

However, we did observe a significant negative relationship between AOI gaze proportion and students' self-reports about whether they would find it difficult to disengage from their thoughts. In other words, if participants spent less time looking at the text, they found it easier to disengage from their thoughts; finally, this relationship was more robust using a larger window of data.

Table 2: Relationship Between Gaze Behavior and Probe Measure by Number of Preceding Paragraphs

		Task Unrelated Thought		Difficulty Disengaging	
	Paragraphs	β (SE)	z (p)	β (SE)	z (p)
AOI Gaze Proportion	1	0.10 (0.31)	0.34 (0.733)	-0.81 (0.44)	-1.85 (0.064)
	2	0.27 (0.35)	0.78 (0.433)	-1.29 (0.55)	**-2.36** (0.018)
	3	0.37 (0.36)	1.03 (0.301)	-1.42 (0.59)	**-2.41** (0.016)
	4	0.37 (0.40)	0.91 (0.361)	-1.54 (0.66)	**-2.33** (0.020)
Offscreen Gaze Proportion	1	0.24 (0.28)	0.87 (0.382)	0.44 (0.36)	1.23 (0.219)
	2	0.20 (0.29)	0.69 (0.493)	0.51 (0.38)	1.34 (0.180)
	3	0.16 (0.30)	0.54 (0.589)	0.53 (0.39)	1.36 (0.176)
	4	0.15 (0.31)	0.48 (0.630)	0.50 (0.40)	1.24 (0.215)

Bold font indicates statistical significance

Table 3: Descriptives of Average Gaze Behavior by Reading Condition

Reading Condition	n	Total Gazes	AOI Proportion	Offscreen Proportion
Never Read	25	579.37 (331.27)	.24 (.19)	.34 (.21)
Previously Read	18	441.3 (161.71)	.14 (.10)	.48 (.21)

3.3 Gaze behaviors and prior reading

We then examined if gaze behaviors are sensitive to text familiarity (research question 3) by looking at the effect of prior reading of the text on gaze behaviors during reading. Research question 3 was addressed using a similar linear mixed effects model approach as research question 2. Specifically, we determined whether gaze behaviors were sensitive to whether the text had been read before by regressing gaze behaviors on reading condition as a fixed effect. Once again, random intercepts for participant and paragraph were included.

Table 3 shows average gaze proportions by reading condition. Participants that previously read the text before had a lower AOI proportion, β = -70.90, SE = 33.93, $t(39.89) = -2.09$, $p = .043$, and greater offscreen proportion, β = 0.15, SE = 0.07, $t(49.96) = 2.15$, $p = .038$, than those that had never read the text. However, no significant difference was observed between conditions in number of gazes, β = -136.86, SE = 87.11, $t(39.89) = -1.57$, $p = .124$. These results suggest that having read the text before affected on-task reading behavior negatively.

Because of the difference in AOI proportion between the two conditions, an additional analysis was performed to examine if reading the text before moderated the relationship between AOI proportion and disengagement. The same generalized linear model as the prior analyses of the relationship was used with the addition of reading condition as a fixed effect. This analysis was performed using gaze behavior from two paragraphs before each probe. Lower AOI proportion was still associated with higher ratings of disengagement, β = -1.47, SE = 0.66, $z = -2.22$, $p = .027$, and no significant interaction was observed, β = 0.46, SE = 1.20, $z = 0.38$, $p = .703$, suggesting that having read the text before did not moderate the relationship.

4 DISCUSSION

Decades of eye tracking research is now being made more available for scaled use for research and practice, with the introduction of more affordable methodologies for tracking eye movement. Of particular interest to the field of Learning Analytics, such methodologies allow gaze tracking to be done in ecologically valid environments. For years, the often obtrusive and expensive equipment required to conduct eye-tracking has relegated this research to be conducted in the lab. This has meant that despite the known connections between eye gaze and educationally-relevant cognitive states, there have been limited studies using eye gaze for learning analytics in the environments where learning typically happens, and these technologies have not been used to improve learning in practice, particularly for neurodiverse students. This study thus explored how a more recent webcam-based gaze tracker (WebGazer) can be used to monitor the eye movements of neurodiverse students, with the goal of setting the foundation for learning analytics and adaptive applications that can better support their learning. In the remainder of this section, we discuss our main findings, consider potential applications, and discuss limitations and future work.

4.1 Main Findings and Novelty

The present study examined if webcam-based eye tracking can be used with neurodivergent students in an ecological setting. Webcams have consistently been shown to be less accurate than more traditional research-grade equipment. Similarly, gaze tracking is typically less accurate outside of the lab, with additional noise presented by ecologically valid environments (e.g., increased distraction, variable lighting, etc.) Despite these challenges, we have found that a webcam-based eye tracker can be used to monitor reading behavior with neurodiverse students.

Turning to our second question, we also found that AOI gaze proportion (i.e., looking to the most important areas on the screen) was negatively correlated with students' difficulty disengaging from their thoughts—a well-known part of the symptomatology profile for neurodiverse individuals. This suggests that it may be feasible to detect in real-time when students experience certain thought patterns (i.e., getting stuck in their thoughts), making it possible to eventually intervene. Finally, we also found evidence that a webcam-based eye-tracker is sensitive to reading behaviors, such as familiarity with the text; students who had read the text before had different gaze behaviors, marked by lower AOI gaze proportion than those that had not read the text before, suggesting that less time was spent looking at the text when rereading. This is further evidence that even a stock webcam can be used to glean reliable information from students reading behaviors, even in a "noisy" traditional classroom setting.

4.2 Applications

The finding that gaze locations are associated with different dimensions of online thought for neurodivergent students provides promise that webcam-based eye trackers could be used to develop real-time interventions. Interventions to support learning can take a number of forms: they can be subtle and thus not noticed as an explicit adaptation by the user, or more overt, where the user is aware of the adaptation or that the software detected something from their interaction. For example, a more subtle intervention may make minor adaptations to instruction, without explicitly acknowledging that a student was not engaged (e.g., [52]). In contrast, D'Mello et al. [27] used a more overt intervention where an agent in the learning environment directly addressed the student, acknowledging that their attention may have wandered in the last 30 seconds. These are just two examples, and research will be needed to evaluate the appropriate method of intervention for TUT for this student population.

The current data provide validation and a "proof of concept" that webcam-gaze monitoring can be effectively employed with neurodivergent students in higher education. Bringing attention and awareness to moments of inattention holds tremendous promise as an effective, minimal resource and minimal cost "intervention" for neurodivergent individuals or students in general who experience lapses of executive function. General approaches that bring attention to one's thinking i.e., strategies that fall under the broad category of metacognition and/or mindfulness practices have been evidenced to support individuals with executive function challenges [45, 77].

Any learning intervention must consider the fact that there are inaccuracies in the gaze monitoring and subsequent user modelling. A gaze-based detector might inaccurately assert that a student is in a certain state when they are not (false positives) or it might assert that a student is not in that state, when in fact, they were (false negatives). Detection and user modelling does not need to be perfect as long as this is accounted for in the response from the learning software. Prior work has attempted to mitigate this problem with a probabilistic approach, using detector confidence as a likelihood [38, 52]. This likelihood will guide whether an intervention is launched (i.e., if the confidence of an intervention being needed is 70%, there is a 70% chance that an intervention will be triggered). In addition, interventions should be designed to be "fail-soft" in that there are no harmful effects if delivered at an incorrect time.

This technology also has promise for teacher feedback and instructional design. Eye gaze has consistently been shown as a successful measure of engagement, comprehension, and confusion. This work has demonstrated the potential of a cheaper alternative to traditional gaze trackers for use in ecologically valid spaces such as classrooms. As such, it may be possible to leverage the scalable technology to implement gaze metrics of the above constructs—previously developed in the lab—in the classroom and provide formative feedback to teachers and instructors through learner dashboards. This feedback can allow teachers to identify needs in individual students, as well as trends across a group. Such trends may be related to a specific piece of learning material or activity and could provide teachers with insights in how to improve the instruction they offer. In addition to these potential applications, it is also important to consider what this technology should *not* be used for. The variance in accuracy between users demonstrates that though this technology may give a valid and useful signal, it is not 100% conclusive. Therefore, this approach is not suitable for summative evaluation or as a decision-making metric in isolation. Using this approach alone to drive a decision could result in penalizing a student for a technology limitation. Instead, this methodology should be added to the ensemble of methods used by teachers and instructors to make decisions and support the learning of their students.

4.3 Limitations and Future Work

Like all studies, ours has limitations that we hope to address in future work. Firstly, as data collection occurred in an ecologically valid setting, we were not able to collect a comparison dataset with a "gold standard" eye tracker. This, in turn meant that we could not use statistical methods to assess the validity of Webgazer's calculations of gaze location; instead, it was necessary to rely on visual inspection of the gaze data. Webgazer has previously been evaluated for accuracy, whereas the present study was designed to test if the predictions of gaze location reported by Webgazer can be used to assess behavior, not how accurate the predictions were. Figure 4 provides an example of when a more refined test is needed when assessing issues with Webgazer. Further research needs to be performed to better assess accuracy and if differences exist when compared with a neurotypical sample. Prior gaze tracking work has shown success for modelling student behaviors and cognitive states without accurate relative gaze locations assuming the calculation of gaze features such as fixations was unaffected [1]. As such, future work should also consider if the variation in accuracy has a meaningful impact on user modeling.

Secondly, additional understanding of Webgazer's limitations in ecological settings is needed. In the present study, lighting differences in the classrooms corresponded to reading condition, i.e., participants that had read the text before performed the experiment in the one classroom with no natural light. There has been some research that shows Webgazer's ability to make accurate predictions is affected by factors such as lighting [17]. There may be other moderating effects both from the participant (e.g., eye color, wearing glasses or contact lenses) and the environment (e.g., background contrast) that may also affect Webgazer. Now that this work has demonstrated the initial feasibility of Webgazer for use with neurodiverse students, future work should consider the impact of additional moderators, and if these moderating effects are the same as seen with neurotypical individuals. It is also important to mention that webcam-based eye-tracking may bring up issues of privacy. Our solution did not collect any images or videos whatsoever, but it is possible that there may be vulnerabilities introduced simply by asking students to uncover their cameras, etc.

The study was also limited in the comparisons that could be made. Because of co-morbidity, comparisons of thought dimensions and gaze behavior between different diagnoses could not be made due to insufficient power. This work also did not collect a comparison sample of neurotypical students. Future work should consider additional data collection, so that we can evaluate whether webcam-based eye tracking performs differently between neurodiverse and neurotypical students. In doing so, it may also be valuable to collect a larger sample of neurodiverse students, so that we can differentiate results between students with different forms of neurodiversity. Such research will help inform the field of differences we need to be aware of and can in turn inform the design learning environments and detectors for students. Future research questions should include questions about whether detectors of cognitive constructs, such as mind wandering, have equitable performance across both neurotypical and neurodiverse students?

A final and critical avenue for future work is in the evaluation of algorithmic biases [44]. The gaze tracking approach used here relies on computer vision techniques which have historically had biases to racial groups more commonly found in the training data [73]. The underlying mechanism for WebGazer is described as being robust to algorithmic bias by its developers, however additional evaluation should be conducted to ensure that this is true in this use case, considering eye gaze specifically (rather than the full-face mesh). A gaze-tracking methodology that is both scalable and robust to individual differences will allow for the implementation of decades of gaze-based research in the classroom and provide additional support to learners.

5 CONCLUSION

The present study examined the validity and applicability of using webcam-based eye tracking as a basis for studying neurodivergent students in educational settings. We provide the first evidence that webcam-based eye tracking may be a viable option for future research and the development of real-time, scalable applications to benefit neurodiverse students. We believe that such work is important; as we begin to leverage technology to understand and design educational technologies, the characteristics of the intended user must be taken into consideration—celebrating the diversity that exists between all of us, and ensuring the inclusion of all learners

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