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UTILIZATION OF BLINK RATE AS A PROXY FOR ENGAGEMENT

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Abstract

This study investigated factors influencing trial engagement by evaluating visual attention, cognitive abilities, behavioral tendencies, and physiological responses. Building on previous research suggesting that blinks play a role in attention modulation, this study focused on exploring blinks as a potential quantifiable metric of engagement. As blinking is an omnipresent and involuntary process, the continuous stream of ocular data observed during experiments offers an opportunity to examine its relationship with engagement. Participants included child and caregiver dyads recruited for a Parent-Child Interaction Therapy (PCIT) study. Eye-tracking data from facial identification tasks completed by both children and caregivers formed the basis of the analysis. Key findings revealed that Time to First Fixation (TFF) and cognitive measures, including the Verbal Comprehension Index (VCI) and Full-Scale IQ (FSIQ), were significant predictors of engagement, suggesting that greater cognitive and attentional efficiency is associated with sustained focus. While greater cognitive ability was linked to efficient attention, participants with lower VCI scores engaged effectively with the task, suggesting a reliance on nonverbal or visually guided search strategies. However, behavioral metrics such as the Eyberg Child Behavior Inventory (ECBI) showed a weaker association with engagement, underscoring the complex interplay of variables that influence attention regulation. The findings emphasize the need for future research to integrate additional physiological and behavioral metrics, such as pupil dilation and saccadic patterns, to achieve a more holistic understanding of engagement. This study contributes to the growing body of knowledge on sustained attention and engagement, laying the foundation for developing more accurate and comprehensive measures of attentional processes.

Background

There has been ample research supporting the notion that the characteristics of eye blinks can be utilized as a behavioral marker for various internal processes, including attention (Hoppe et al, 2018). This notion can be further supported by subdividing metrics of blinking to observe blink rate and duration on behavior and mood modulation.

In the past, calculating the blink duration once proved to be onerous and complicated. By including multiple modalities and extracting blinks through continuous eye-tracking data, researchers have proposed a model to determine the minimum threshold for blink quantification and apply task-related blink data to quantify cognitive states, for example, mind wandering (Hollander et al., 2022). Moreover, spontaneous blink data in studies has proved to be an inexpensive and innovative biomarker of central dopamine functioning in the brain, which affects memory, habit learning, and reward association (Jongkees et al., 2016). Given that task-related blink data has been utilized in many studies to understand specific behavioral processes, blink dynamics may also be useful in interpreting other cognitive states, such as active attention modulation.

Blink Rate

Blink rates can increase throughout childhood to adulthood; it is estimated that adults blink around 13,500 times a day (Homke et al., 2018). Eye blinks can be differentiated into three categories: reflexive, voluntary, and spontaneous. Voluntary blinks involve the subject performing consciously, while reflexive blinks are produced through external stimuli (bright lights or rubbing of the eyes). Spontaneous blinks tend to occur without the need for stimulation, meaning that the data observed is a continuous stream (Espinosa et al., 2020). Previously, blinking was assumed to be a process that hindered the stream of visual content. Humans tend to blink frequently despite temporarily blocking visual input. When observing the timing and frequency of blinks during cognitive tasks, it seems that blinking takes on a more complex role due to its contribution to attention and perception (Yang et al., 2024). Although traditionally, blink rate has been assumed to be a reflexive procedure and primarily associated with ocular lubrication, there is also evidence that blink rate can be indicative of cognitive load (Homke et al., 2018). Some studies have shown that participants blink more under situations that entail smaller cognitive loads compared to larger cognitive loads. Moreover, blink-related neural processes are suggested to be modulated through both internal cognitive loading and external sensory criteria (Liu et al., 2017). Therefore, it has been suggested that a tradeoff exists between the obstruction of visual input caused by blinking and a theorized purposeful role that blinks have beyond ocular lubrication (Yang et al., 2024).

Moreover, several behavioral studies show that blinking can deactivate the dorsal attention network and activate the default mode network during social attention tasks (Homke et al., 2018). These findings suggest that blinks may be involved in attentional disengagement. Considering that blinking is an omnipresent and involuntary process, it would be beneficial to investigate the role that task-related blinks can play in attention modulation, as we can observe the constant stream of ocular data during experiments as a quantifiable engagement metric. This would allow for greater validity of predictions regarding a single participant's cognitive functioning and attention allocation during behavioral tasks. Since blinking is non-invasive and relatively economical to measure, it would provide greater ecological validity in addition to understanding engagement.

Attention

In neurological diseases such as Parkinson's disease and schizophrenia, spontaneous blink rate is linked to striatal dopamine activity. In normative samples, individual variations in spontaneous and task-related eye blink rate are correlated with working memory task performance, working memory gating, attentional load and fatigue, and attentional control (Ranti et al, 2020). This notion can be further supported through spectral analysis of EEG data focusing on post-blink latency as the appearance of early power increases in delta and beta/ low-gamma frequency bands (12-35 Hz) which represents the response to visual processing caused by blinking. Furthermore, this is followed by a later and longer power decrease in alpha (7-13 Hz) and theta (4-7 Hz) bands which can be attributed to information processing and episodic memory (Liu et al, 2019). Moreover, blinks can activate the precuneus regions that correlate with environmental monitoring and awareness (Ranti et al, 2020). Based on the evidence seen in previous research, blink rate plays a role in cognitive functioning and can provide ample scope to understand specific cognitive processes such as attention modulation (Yang et al, 2024).

However, it is important to note some discrepancies in the literature regarding spontaneous blink rates and dopamine synthesis. Some studies have discovered a lack of correlation between spontaneous eye blink rate and striatal dopamine synthesis capacity. There is a possibility that the spontaneous eye blink rate may not be a reliable proxy for dopamine synthesis capacity in the striatum (Sescousse et al, 2018). In addition, some studies have suggested that spontaneous eye blink rates may not be correlated with D2 receptor availability and may not accurately reflect D2 receptor availability (Dang et al, 2017). Moreover, dopamine's influence on cognition may be more complex and indirect, as at least one study provides evidence against previous assumptions linking dopamine synthesis with spontaneous eye blink rates and key behavioral traits (van den Bosch et al, 2023). Though this evidence may suggest a less meaningful relationship between spontaneous eye blink rates and cognitive performance, these findings do not invalidate our approach, as this project will focus on observing task-related blink rates in relation to task engagement.

Blink rate is not only associated with neural regulation in the dorsal attention network and precuneus, but other forms of blink metrics can also be linked behaviorally to mind wandering. For example, longer durations of task-related blinks can be utilized as an indicator of mind wandering (Hollander et al., 2022). This phenomenon highlights the importance of both blink rate and duration, which are necessarily linked, to engagement. One theoretical explanation for this relationship is that individuals will be inclined to blink less when what they are viewing is perceived to be important (Ranti et al, 2020).

There is an underlying assumed tradeoff regarding blinking between the internal, physiological need to blink to lubricate the eyes versus the external task component to concentrate on important task-related information and allow the least interruption of the visual stream by restraining from blinking. From this notion, we can potentially predict that by concentrating on more valuable material, there will be a decrease in the blink rate overall, within physiological limits. Given the evidence of a cognitive component to task-related blink rate through the activation of the default network and an attentional component to blink duration, one potential avenue of exploration would be to examine whether task-related blink rate patterns can provide proximal information regarding the extent to which viewers are engaged in what they are viewing, and further predict behavioral consequences (e.g. task performance) of engagement level. Future research is needed to determine if instantaneous blink rate can be utilized, for instance, to index moment-by-moment variation in engagement (Ranti et al, 2020), and whether the blink rate could be extended as an additional manipulation check on task engagement for the study design and interpretation of behavioral results.

The calculation of blink rate is a complex process, as are various components required to assess what qualifies as an individual blink. Current eye trackers are unable to directly report whether the occurrence of data loss is due to blinks or is attributed to inaccuracy in calibration, head movement, or fixations made offscreen. Hence, it is important to include a range of what can be characterized as a blink and establish a minimum blink threshold.

One proposed solution to this problem is the inclusion of multiple modalities as well as computing blink rates through eye-tracking data. We define a blink as having data loss occur in both eyes. However, this is a simplistic definition of an eye blink, and as mentioned above, there are various potential causes for data loss. One purpose of this study will be to investigate parameters that can be used to characterize eye blinks from other forms of data loss and develop an operational definition for eye blinks from eye-tracking data.

Negative Emotion Stimuli

There have been many studies regarding negative emotion perception and negative emotional stimuli on behavior. Emotional states can influence attention in individuals (Tyng CM et al, 2017). Some studies have shown that negative stimuli can attract attention due to potential evolutionary needs to detect threats (Fox et al, 2007). There has been ample research regarding observing emotion perception and mood dynamics. Findings from such studies have indicated that greater attentional bias towards threatening stimuli can be explained by greater reactivity to stressors (Naim et al, 2015).

There is great interest in observing the relationship between emotional states and behavioral control; however, the literature is sparse on the relationship between negative affect and blink regulation specifically. Spontaneous blink frequency has been associated with heightened emotional states, particularly negative emotions (stress, anxiety, and fear) (Kret et al, 2018). Some previous research has postulated attention and emotion as two separate, non-interacting processes; however, the motivational relevance of the stimulus can exert a strong influence over cognitive processing (Mueller et al, 2011). Since it has been established that blinking is a physiological mechanism that aims to minimize information loss, emotional content as a highly relevant stimulus may mediate the relationship between attention and blink frequency. Moreover, the task-related blink rate or duration may indicate task engagement in a more general sense and provide additional insight into factors influencing emotional processing during tasks specifically targeting this construct.

Purpose and Research Objectives

The origin of this study was rooted in discerning whether emotional attention bias could serve as a biomarker of emotional processing and literacy concerning childhood behavior. Adverse Childhood Experiences (ACEs) are known to disrupt emotional processing and can lead to negative life outcomes (Herzog et al., 2018). To predict the consequences that may result from ACEs, it is important to understand the child's outcomes based on the influence of the functional capabilities of the caregiver as well as the behavioral impact this may have on the child. The study from which the current data was derived was focused on observing how emotional literacy in caregivers may mediate the relationship between the variables of attention biases with trauma exposure, externalizing behaviors, and caregiver emotional processing capacity and future behavioral outcomes. The eye-tracking component was utilized to noninvasively address physiological components of attentional bias across caregiver-child dyads that may not be conducted effectively through alternative methods such as EEG. The purpose of the eye tracker was to clarify the physiological foundation of biased attention when in the presence of negatively valenced emotional stimuli that reside in maladaptive caregiver-child relationships.

Although the purpose of the previous study was to gauge the effect of caregiver emotional literacy on attention biases and externalizing behaviors, the eye-tracking data from this study may be effective in assessing the relationship between task-related blink rate and negative emotional stimuli in caregiver-child dyads as well as gathering insight into the functional capabilities and behavioral implications that caregiver engagement has on their children's emotional processing. These findings could provide greater translational potential as they could provide scope for observing outcomes on an individual level.

To further explore this relationship, we proposed to study task-related blink rate and task engagement by breaking down the single trials for both the adult and child participants and establishing a pattern within the data that is indicative of blinks. Additionally, we proposed to discriminate between the individual trials and see if regions of prolonged data loss beyond that commensurate with blinking follow a pattern indicative of overt lack of engagement during the task that is consistent with task performance. There is scope to explore this notion as this literature has shown that quick overt eye fixations may lead to disengagement in children during the presence of negative emotional stimuli (Sabatos-DeVito et al., 2016). This would aid us in understanding the participants' engagement on an item level during the task as well as determine their engagement during the appearance of emotionally charged faces. To expand upon the trial-by-trial level, we also wanted to observe task engagement in a more general sense by comparing relationships between severe disengagement (data loss due to saccadic eye movements away from the screen entirely) and blinking during times of task engagement observed at the trial-by-trial level. Moreover, was there an effect on the physiological data (blink rate or blink duration) preceding major disengagement in the participants compared to trials with no disengagement?

Based on our initial findings, we anticipate the presence of higher blink rates will occur in the presence of negative emotional stimuli, indicating increased attentional disengagement among both child and caregiver pairs. Furthermore, we expect variations in blink rates leading up to significant disengagement events.

Methods

Participants

The participants in the study were child-caregiver dyads (N=61) recruited from the Child Study Center at the University of Oklahoma Health Sciences Center (OUHSC). The parent-child dyads participated in a PCIT study at the Child Study Center at the time of recruitment. The children ranged between the ages of 3 to 7 (mean age 5). The caregivers ranged from the ages of 27 to 66 (mean age 43). There were more male child participants than female child participants in the study (M=31, F=10) and more female caregivers than male caregivers (M=6, F=29; 13 caregivers participated with multiple children, 13 caregivers chose not to participate). Families were patients at the "A Better Chance Clinic" where the children either had a history or suspected history of prenatal substance abuse during the period of recruitment into the program. The caregivers were either the biological parent, the foster parent, or the adoptive caregiver of the child.

Materials

The child-caregiver dyads completed a series of assessments (either self-report or clinician, informant consistent within measure) which included a Peabody Development Motor Scales (PDMS-2) (Folio R et al., 2000), Full Scale IQ (FSIQ) (Weschler, 1981), Eyberg Child

Behavior Inventory (ECBI) (Early Intervention Foundation, 2020), and the Bayley Scales of Infant and Toddler Development (Bayley III) (Bayley, 2005). The participants provide demographic information for themselves and the child. In the case of not being the biological parent, information was provided by the caregiver regarding the biological parents of the child. Both child and caregiver then completed separate but similar emotional facial expression eye-tracking tasks.

The Tobii T120 screen-based eye tracker was utilized to measure "attention with participation" occurring during task performance. For the study, the stimuli were sourced from the NimStim Face Stimulus Set. This database includes images that are diverse in the inclusion of multiracial actors and is readily available to the scientific community (Tottenham, 2009). Each set of photos includes the same actor making 7 different emotional facial expressions. This set of stimuli is valid and reliable for the accurate identification of emotional expressions (Tottenham, 2009). The stimuli development and presentation were conducted through the Tobii Pro studio and were run through the Tobii T120 eye tracking system at a sampling rate of 60 Hz. A 17-inch monitor was used to display the images to the participants. Infrared sensors embedded in the lower edge of the eye-tracker screen used pupil center corneal reflection to track the center and size of the pupil and corneal surface reflection to gather the position of the participant's gaze from both eyes.

Eye-tracking Procedures

Caregivers provided written informed consent with child assent for the study during clinic intake and prior to the eye-tracking task. Clinical assessments and demographics were gathered before participation as part of a larger ongoing research study. Participants provided information regarding ocular vision (ex., Astigmatism, cataracts, glaucoma, etc.) as well as whether they used corrective lenses. All the participants either had normal vision or were corrected to normal vision. There was a child task and a caregiver task administered to the children and caregivers, respectively.

Caregiver Task

The task began after the eye gaze location of the participants was calibrated. With the Tobii computer monitor 60 cm away, the participant was provided with a wired mouse connected to the stimulus laptop. The participants were instructed that for the task, they needed to continually look at the screen without moving their heads and orient their eyesight to the white cross (fixation point) on the screen until they progressed to the next trial. Once a face stimulus (ex. trial) was presented, the participant was required to match the target emotion with the target word located in the middle of the screen and click with their mouse on their chosen option (Fig.1). Caregiver tasks were designed to contain 5 practice trials and 120 trials where 20 trials were allotted for each target emotion. Each of the face stimuli represented a different emotion (happy, disgust, sad, angry, fearful, and neutral), and the target word was centered in the middle of the screen. The target word replaced the central fixation point and would return in between trials to allow for reorientation of the participant's gaze to the middle of the screen.

Caregiver Task

Figure 1: Example of caregiver trial administered to the adults.

Child Task

The child task was designed relatively similarly to the caregiver task with the distinction being that the children were instructed to find a face that expressed a different emotion from the rest of the presented face stimuli. Unlike the caregivers, the children were not required to make any selections when the target face was located (Fig.2). The purpose of this distinction was to allow the child to regulate the amount of time they would spend fixating on the negative emotions once they made their decision. The child task supplemented a smiley face fixation point for the white cross fixation point and had fewer trials (5 practice trials and 60 trials). Only negative faces were utilized as the target emotion for the child task where the participants were tasked with identifying stimuli with the emotions of sad, anger, and fear among 5 neutral faces (Davies et al., 2018)

The Tobii eye-tracking system was equipped with a 60hz sampling rate and collected the raw eye movement data points of the participants. Every data point was recorded with a timestamp and coordinated with the corresponding eye gaze point locations. A criterion of 50% of recorded data from all the trials for each participant was required to be included in the analysis. Any missing eye-tracking data was not replaced or interpolated. The literature has shown that children from high-conflict homes tend to process facial emotions differently compared to children from low-conflict homes (Briggs-Gowan et al., 2015; Davies et al., 2018; Schermerhorn et al., 2015). Attention biases, time spent on viewing negative and neutral facial expressions, time spent viewing positive faces, and time spent viewing each area of interest (AOI) type (eyes and mouths) were calculated for each participant to understand the emotion processing capacity of both the child and caregivers.

Child Task

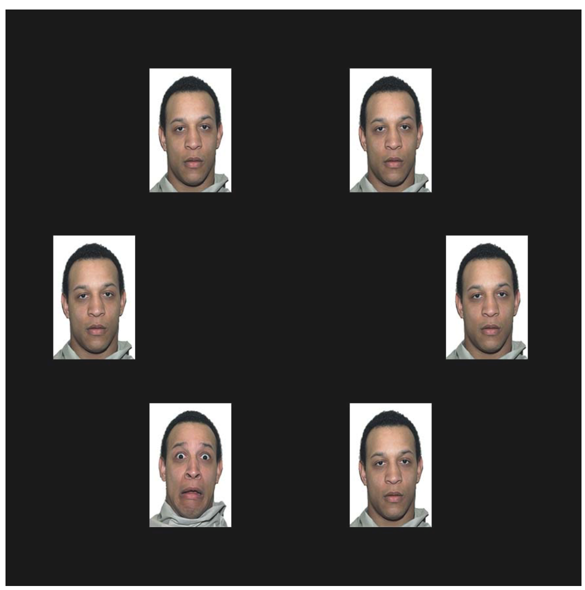

Figure 2: Example of the Child trial administered to the children.

MATLAB Analysis

Preliminary analyses focused on the relationship between blink rate and uncoupling of attention toward negative emotional stimuli. Since the missing eye-tracking data collected during the trials were not replaced or interpolated, we predicted that the missing data within physiological bounds appropriate for characterizing eye blinks (see parameters below) could indeed represent the eye blink of the participants. The methods regarding continuous eye-tracking data are novel as gathering information throughout the continuous stream of ocular data is onerous and complicated. For calculating the blink durations and rates for each participant, we incorporated a MATLAB code from a previous paper whose model was similar to the current study (Hollander et.al, 2022). This code extensively analyzed the stream of ocular data including the portions of missing data to assess the overall blink rate for each participant. As mentioned above, an exclusionary criterion was also applied to the analysis which included a minimum threshold for eye blinks to exclude measurements that could not be feasibly accepted as a blink. For our analysis, we kept the same criterion of what can be accepted or rejected as a blink. Although measurements that do not fall within the inclusionary criterion were excluded from the analysis, there still may be ample scope to observe this measurement; particularly the longer measurements as these may be informative of behavior. To calculate blinks, we analyzed the measurements of the eye positions of the left and right eye as well as the measurements of the left and right pupils. Missing data in both eyes simultaneously that occurred within the specified time range was characterized as a blink. We then calculated the duration of a blink event and the number of blinks, which were then divided by the total task time to obtain the blink rate (blinks per second). Spearman correlations were run between the target eye tracking task performance variables (time spent on viewing negative and neutral facial expressions, time spent viewing positive faces, and time spent viewing each area of interest (AOI) type (eyes and mouths) and blink rate to assess the relationship between blink rate and the presence of negative emotional stimuli. The variables were recorded as raw scores for both the behavioral and clinical data.

Assessment variables, which included FSIQ (Koriakin et al., 2013), Peabody Development Motor Skills (Folio et al., 2001), Eyberg Child Behavior Inventory (ECBI), and Bayley Scales of Infant (BSI) ((Bayley et al., 2005), were also included in the analysis to assess the presence of a relationship between behavioral variables for the children and their respective blink rates and blink duration.

Single Trial Analysis

To expand upon the analysis centered around attention toward negative emotional stimuli, we proposed to investigate blink rate patterns relevant to moment-to-moment task engagement. While blink rate could be a gateway to providing insight into the emotional processing of the caregiver and child dyads, attention is not a static construct; therefore, exploring task engagement at the individual trial level may be informative. By analyzing the single-trial files for each participant, we wanted to observe not only blink variables associated with specific trial types but also begin to incorporate information regarding longer periods of data loss, which were unlikely to be blink related. These periods of data loss represent one of two occurrences: 1) they may be true loss of recording for one or more pupils, or 2) they may represent participants moving their eyes or heads out of the viewing area of the eye tracker, thus engaging in overt attention re-allocation away from task stimuli. Typically, equipment-related data loss is due to reflections from corrective lenses, reduced contrast between pupil and iris for specific iris colors, and other physical disconnections between the infrared sensor and eye gaze. These types of data loss are often for only one eye at any given time and are abrupt (not preceded by any goal-directed eye movements toward the edge of the screen). Attention-related data loss, in this case, was defined as any data loss likely to be from overt eye or head movement away from the screen (Sabatos-DeVito et al., 2016). This type of data loss needed to involve a complete loss of recording from both eyes and had to immediately be preceded by fixation or saccadic eye movement toward the edge of the screen.

The parameters for attentional disengagement were stringent towards ensuring that the data loss that is included in the data analysis is solely due to disengagement during the trials. Since our previous blink range is set at 83 ms to 1000 ms, any measurements that are less than 1000 ms were not considered disengagement as they fell within the range of blinking. Therefore, our minimum threshold for disengagement was considered greater than 1000 ms. Attentional disengagement in datasets with at least 50% data retention is likely to only range for a few seconds at any one time, indicative of short but sustained voluntary disengagement during an otherwise compliant behavioral performance; we began the analysis by setting the maximum threshold for disengagements at 5000 ms. However, the exploratory data-driven analysis was performed by stepping the maximum threshold by 500 ms up to the maximum reported range of data loss to investigate the most informative threshold correlating with behavioral performance. Participants could have engaged in inattention without looking completely away from the screen, resulting in a lack of task processing without subsequent data loss. Blocks of inattention that met this criterion were defined as any time the participant's eye gaze was fixated outside of the circular coordinate system of the stimuli. We had the exact eye coordinate positions for the participants during the trial, which we used to gather information about where the participants' eye gaze and position were during the individual stimuli. Furthermore, we defined disengagement to occur when the participant's eye positions show the participants outside of the coordinate system of the stimuli and traveling towards and/or off the screen and then returning their eyes to the screen, inside of the coordinate system that contains the stimuli. This data loss was quantified for analysis and coded as attentional disengagement.

For our eye blink detection and calculation methodology, blinks were defined as occurring within the time range of 83 to 1000 ms. Any measurements that fell outside this range were not considered as blinks. Instances of consecutive missing samples were accounted for by multiplying the number of missing samples by a factor of 17, converting the measurement to milliseconds (ms). Although previous research has established a consensus on accepting a maximum threshold boundary of 1000 ms for blinks, the lower blink threshold parameter remains a topic of debate (Hollander et al., 2022). To determine whether blink counts are differentiated based on different threshold parameters, we modified the blink parameters in the script. We did not observe a significant difference in the blink counts when the lower or upper threshold values were modified. Therefore, consistent with our initial analysis (Hollander et al., 2022), we maintained the same cutoff value of 83 ms for blink analysis.

Statistical Analysis

To understand task performance during the single trials, we defined specific variables to gauge performance based on disengagement. For the caregiver trials, we wanted to compare the caregiver accuracy in identifying the stimuli and disengagement for each trial. The child trials were analyzed differently as we did not have a measure of accuracy towards the accuracy of the stimuli identification. For these trials, we focused on the amount of time fixated on the stimuli (specific negative valanced face) and the child disengagement during the trial.

For our analysis, we ran multiple regression analyses for only the child data. In the model, we had time for the first fixation on the stimuli (TFF), the length of fixation count (FC), the child disengagement duration, emotion, and an interaction variable between emotion and disengagement duration. The goal of the child analysis was to observe the time to first fixation on the correct target based on disengagement. We believed that the analysis would differ based on emotion, consistent with previous findings of preferential disengagement to angry faces after first fixation (Davies et al., 2018). Since we did not have an accuracy measurement for the child data, we looked at the specific eye-tracking behavior and disengagement between the trials. The trial time was the same for each trial. The length of each trial and the inter-trial fixation points were equivalent to 5000 ms. Therefore, for our analysis, we proposed that the parameters for attentional disengagement would be between 83 ms and 5000 ms.

Our analysis could essentially aid in bridging the gap between our understanding of how physiological functioning (ex., blink functions) can affect cognitive processing. Similar to the methods described in the MATLAB analysis section, we modified the script to analyze the trials individually for the participants to isolate blinks in the eye-tracking data.

Results

Blink Rate, Blink Duration, and Behavior

We successfully captured and measured the overall blink rate for the participants and compared that to the behavioral data collected during the trials. This analysis aimed to observe differences between the responses toward the stimuli, providing insight into the parents' emotional processing vs. the children's. Spearman correlations were computed between the clinical and behavioral variables measured in the PCIT study against the blink rate and blink durations. The analysis showed a positive correlation between the Full-Scale Intelligence Quotient (FSIQ) and child blink rate (rho=.484, p=.001), but a negative correlation was displayed against the variables of FSIQ and adult blink rate (rho=-.332, p=.034). There was a positive correlation between the Fixation Counts (FC) for the negative emotional stimuli (Sad (rho=.543, p=.001), Fear (rho=.303, p=.047), Angry (rho=.456, p=.032), and the adult blink rate. Positive correlations were also observed for the Total Fixation Duration (TFD) of specific regions on the face (Mouth (rho=.326, p=.022) and Eyes (rho=-.365, p=.036)) of negative emotional stimuli versus adult blink rate. There were few correlations between blink rate or duration and positive emotional stimuli. These analyses showed a relationship between the fixation of negative emotional stimuli and the presence of a higher blink rate for the caregivers, which could potentially mean that the caregivers were engaging less in the task during the presence of these specific stimuli.

Blink Disengagement Event Results

Adult Analyses

We planned to compare the trial-by-trial variation in attention disengagement against behavioral performance data that we collected for the caregivers. Given that the caregiver's responses on the accuracy of choosing the correct face were collected during the PCIT study, we aimed to compare the responses during the individual trials against the trial-by-trial disengagement to observe how engaged the participants were during the task. However, we found that there were only five adult participants who displayed active disengagement events based on the specified parameters (Table 1). Due to the small number of adult disengagements, we could not execute the multiple regression model designed for the adult data. Though only a few disengagement events occurred for the adult participants, the observed disengagement events occurred primarily towards male faces and negative emotional stimuli.

Participant-wise Disengagement Summary

Participant	*Emotion*	*Face*	*Disengagement Count*	*Disengagement Duration (ms)*
1	Sad	M	1	1579
1	Sad	M	1	2138
1	Angry	F	1	1431
1	Angry	M	1	1809
1	Neutral	M	1	1513
2	Neutral	M	1	1037
3	Sad	M	1	1020
4	Angry	M	1	2549
5	Happy	F	1	2178

Table 1: Disengagement data for individual participants during the emotional face task. For each combination of emotion and face gender, the table includes the disengagement event count and corresponding duration in milliseconds (ms).

Child Analyses

The children's outcomes differed as we had no required behavioral responses during their tasks and thus could not compute accuracy measures. We, therefore, focused analyses on several fixations on the target stimuli during the individual trials against the attentional disengagement observed during the trials. Compared to the adults, we observed more disengagement events for the children (Fig.3), allowing us to run the multiple regression model designed to analyze the child data. To reiterate, the multiple regression model included the predictors *Emotion, Disengagement Duration, Interaction variable (Emotion * Disengagement Duration), Time to First Fixation (TFF), and the outcome variable Fixation Count (FC*). The model was significant ($F(4,147) = 5.492$, $p<.001$), and explained 13.0% of the variance in the outcome variable ($R^2=.130$). TFF was the only significant predictor ($\beta=-10.102$, $p<.001$), which indicates that higher TFF values are associated with lower values of fixation count (FC) (Fig. 4). Emotion (β=4.732, p=.344), Interaction (β=-.001, p=.590), and Disengagement Duration (β= -.0008, p=.989) (Fig. 5) were not significant predictors in the model.

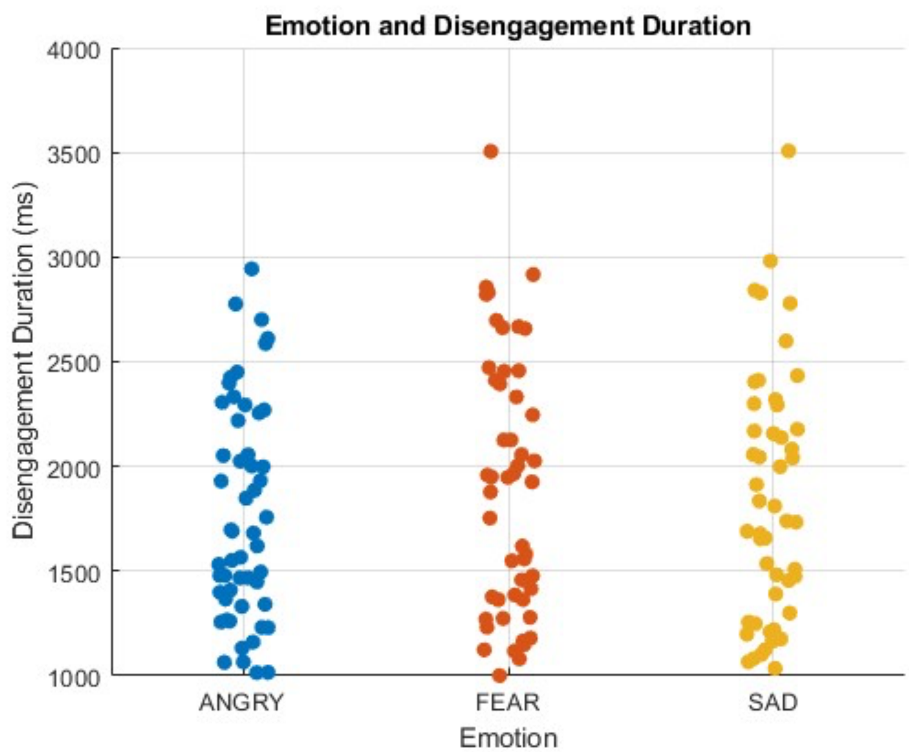

Fig.3: Disengagement durations for the child participants organized by the specific emotion category.

To further analyze the eye-tracking data of the children, we ran several multiple regression models with the behavioral and clinical data collected in the study. We ran a similar multiple regression model using the same predictors, including BASC and ECBI scores, while keeping the same outcome variable (FC). Due to missing data in the behavioral and clinical scores (particularly ECBI scores, which had 30% missingness), multiple imputation was performed using predictive mean matching in R to address data loss. This approach was chosen to preserve the sample size and reduce potential bias. We observed that the model was significant (F (6, 145) = 4.656, $p < 0.001$), and accounted for 15.9% of the variance in the outcome variable (R^2=.159). TFF remained a significant predictor (β=-10.836, p<.001) (Fig. 4), and ECBI scores were an important predictor (β=0.246, p=0.047), which indicates that higher ECBI scores were associated with higher values of FC. BASC scores were not a significant predictor in the model (p=0.262).

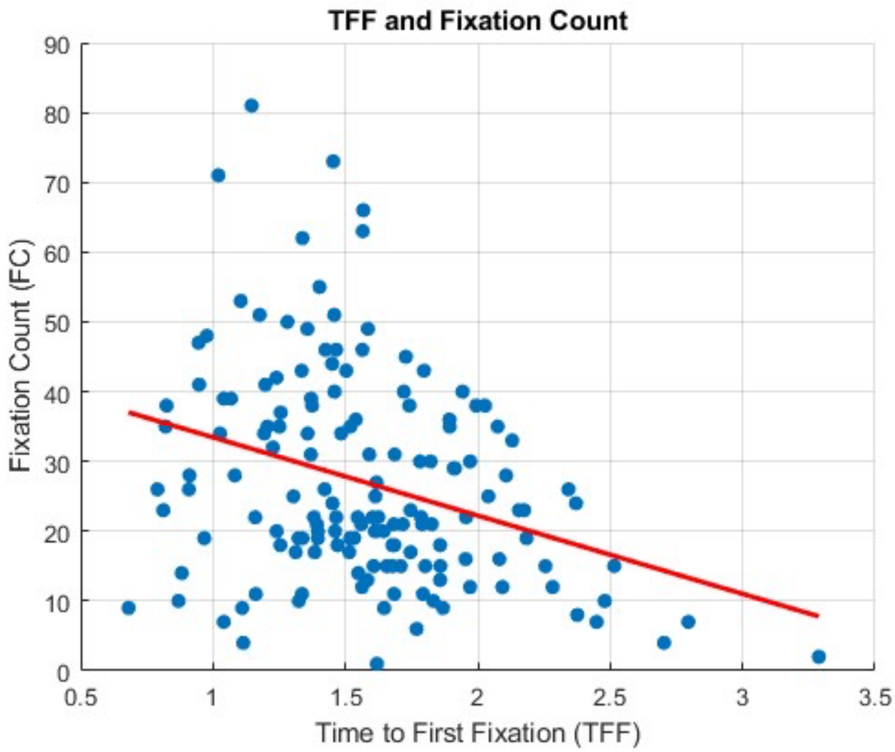

Fig. 4: Time to First Fixation (TFF) decreases as Fixation Count (FC) increases

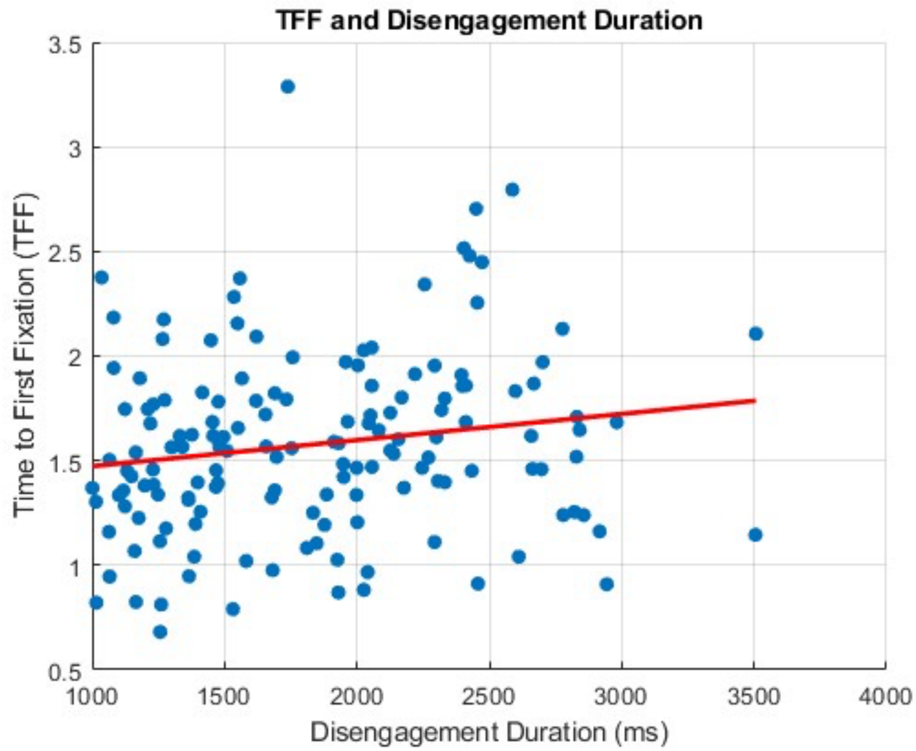

Fig. 5: Time to First Fixation (TFF) does not correlate with disengagement duration (ms).

Another multiple regression analysis was conducted to test the relationship between fixation count and seven predictors: Adverse Childhood Experience scores (ACE), Verbal Comprehension Index (VCI), Visual Spatial Index (VSI), Processing Speed Index (PSI), Full Scale IQ (FSIQ), Functional Reading Independence (FRI), and Working Memory Index (WMI) from the WISC. The overall regression model was statistically significant ($F (7,144) = 4.556$, $p = 0.0001$, $R^2=.181$), indicating that the predictors explain a substantial proportion of variance concerning fixation count. The predictors *ACE* ($p=0.415$), *PSI* ($p=0.069$), *VSI* ($p=0.634$), *FRI* ($p=0.464$), and *WMI* ($p=0.146$) were not statistically significant; however, two variables demonstrated significant individual effects within the model: *VCI and FSIQ*. The variable *Verbal Comprehension Index* (VCI): ($\beta=-0.646$, $p<0.001$) had a significant positive relationship with the outcome variable, as lower VCI scores were associated with higher fixation counts. Full-scale IQ (FSIQ) had a significant positive relationship with FC ($\beta=1.000$, $p<0.001$), which suggested that higher FSIQ scores predicted higher FC values. However, it is important to note that the low R^2 value indicates that the predictors explain only a small portion of the variance in the model.

To determine whether the TFF possibly varied throughout the trials, we averaged the TFF values for the first five trials and the last five trials for each participant and conducted a paired t-test. The results showed no significant difference ($p=0.76$) in the time to first fixation between the first five trials ($M=768$ ms, $SD=363.03$) and the last five trials ($M=784.57$ ms, $SD=410.29$), which indicates that TFF did not significantly change over the trials.

Blink Rate Preceding Disengagement Events

Alongside analyzing disengagement duration on a trial-by-trial basis, we quantified blinks at the single-trial level. We ran a paired samples t-test comparing the blink rate of each participant for trials without disengagements and the blink rate preceding a disengagement event. When calculating the blink rates for both conditions, we observed that some participants had blink rate values within the appropriate range, and some individuals had higher blink rates than the average. Though these blink rates lie within the ranges of possibility, they could also be due to other factors, such as blink flurries or excessive blinking. We calculated the Z-scores for each blink rate and excluded values that were greater than three standard deviations to reduce outliers in our analysis (Fig. 6). Though blink rates were higher in the non-disengagement event condition ($M = -0.729$, $SD = 0.334$) compared to the disengagement event condition ($M = -0.1251$, $SD = 0.335$), the difference was not statistically significant, $t(55) = 1.576$, $p = .121$, 95% CI [-0.014, 0.118]. There was a significant correlation between the two conditions ($r = .735$, $p < .001$), which indicates consistent blink rate patterns across both conditions.

To understand whether the previous behavioral variables could affect the blink rate in the child participants, we ran several multiple regressions. We ran a multiple regression model using the predictors: *Verbal Comprehension Index (VCI), Visual Spatial Index (VSI), Processing Speed Index (PSI), Full Scale IQ (FSIQ), Functional Reading Independence (FRI), and Working Memory Index (WMI*). This regression model was significant ($F(6, 52) = 2.473$, $p=0.035$, $R^2=.222$), with 22.2% of the variance being explained by the predictors as a group, although the individual cognitive indices VSI, WMI, PSI, VMI, VCI, FSIQ were not significant. When comparing these variables against the blink rate preceding disengagement events, the analysis produced similar results as the model does not provide evidence of a significant relationship between blink rate before disengagement and the cognitive indices ($F(6, 52) = 1.78$, $p=0.121$).

A similar multiple regression was run against the blink rate with the predictors of ECBI and BASC scores. This analysis suggested that the model was not significant ($F(2, 56) = 1.762$, p 0.181), and only a small proportion (5.8%) of the variance in blink rate was explained by the behavioral measures. A similar lack of relationship was found between the predictors and the blink rate preceding disengagement ($F(2, 56) = .501$, $p=.608$), with a very small proportion (1.7%) of the variance being explained by the model.

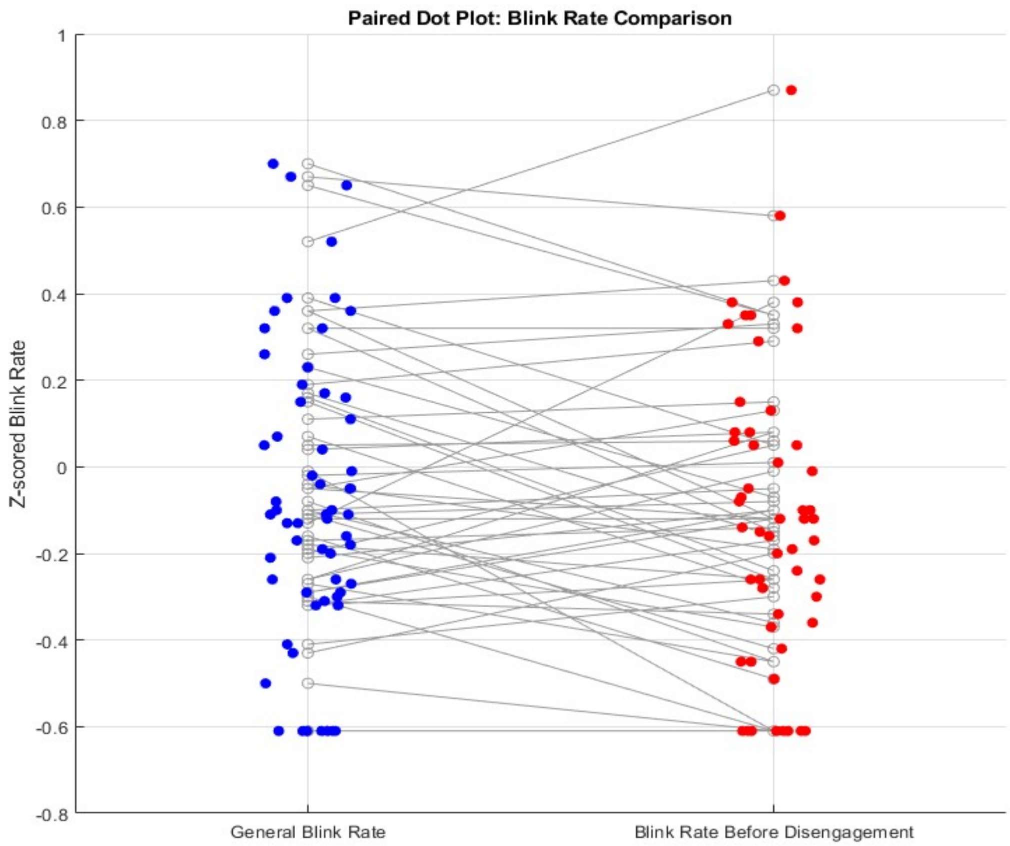

Fig.6: Displays two conditions: the blink rate of each participant before a disengagement event and the blink rate of each participant without a disengagement event (general blink rate). The blink rate values are Z-scored, and only values within 3 SD were included.

Discussion

Based on previous work on blink characteristics and their proposed relationship to specific behavioral and cognitive processes (Hollander et al, 2022), we predicted that our findings in this project would be useful in interpreting attention modulation in the specific population that we are studying. This study is relatively novel as there is not much literature on defining the parameters of disengagement based on ocular data and blink characteristics work has proposed that blink rate was associated with both attentional engagement for emotional stimuli (Sabatos et al., 2016) and with attentional disengagement via reduced visual input and increased information loss (Ranti et al., 2020). As fixation count in our study was positively associated with blink rate, increased blink rate was likely associated with increased cognitive load (Magliacano et al, 2020). Since fixation to mouths is typically considered a less optimal strategy for face identification (Duyck et al, 2021), individuals had to engage more attention (more blinking) to achieve similar performance.

For children, higher blink rates were associated with higher cognitive ability, but the opposite was true for cross-dyad correlations, which implies complex associations between parent-child attentional processing and cognitive ability. Overt attentional disengagement for longer periods was minimal in the adult sample. However, disengagements were primarily in response to male faces and faces displaying negative emotions, which suggests a potential link between the processing of threat and disengagement strategy.

While *Emotion, Interaction between Emotion and Disengagement Duration, Disengagement Duration, and BASC* were not significant predictors, *TFF* and *ECBI* are significant variables in the combined model. Time to first fixation had a significant negative effect, which meant that slower initial engagement with the stimuli was associated with less sustained attention, represented by fewer fixations. This also meant that faster engagement (low *TFF* scores) most likely facilitated better visual exploration, which led to higher fixation counts. Individuals with lower *TFF* could have more efficient attention allocation. Moreover, the findings could reflect that children who exhibited longer times to first fixation engaged less with the stimuli and had slower attentional engagement or reduced motivation to attend to the stimuli. However, overt disengagement durations did not impact fixation counts. This would be consistent with the notion that the children engaged in more covert avoidant behavior characterized by less engagement to intentionally avoid the stimuli while still attending to the task itself (De Haan et al.,2008). We did not find a significant change in TFF across early and late trials within the task for children, suggesting that the effect is static rather than a product of cumulative avoidance due to the emotional toll of negative stimuli across trials.

When analyzing the behavioral variables from the study, higher *ECBI* scores are associated with higher *FC* scores. This could imply that children with more behavioral issues exhibit more erratic visual scanning behavior that results in more brief fixations. Also, it could reflect a lack of sustained attention represented by frequent shifting of gaze (increased *FC*). The high *ECBI* scores could reflect the difficulty children had in maintaining attention or a hypervigilant visual scanning pattern in which the participant continually returns to the emotionally taxing stimulus. Previous literature suggests that socially anxious individuals initially exhibit hypervigilance to threatening social cues (e.g., angry faces) but will quickly shift to avoid these to reduce discomfort (Wieser et al., 2008). Based on these findings, we hypothesized that children who avoided negative stimuli would have more externalizing symptoms and higher ECBI scores; however, the results imply otherwise, as the participants with higher ECBI scores showed more instances of hypervigilance (increased attention) and returned to the stimuli.

The findings overall suggest that attention dynamics, specifically *TFF*, is an important aspect to prioritize for interventions aimed at improving sustained attention. For children with high *ECBI* scores, understanding the relationship between behavior problems and visual scanning could facilitate strategies to improve attention control and engagement. Therefore, investigating how *TFF* and *ECBI* scores relate to other measures of attention (e.g., disengagement duration) could provide a greater holistic understanding of attentional dynamics in children with behavior challenges.

Although disengagement duration did not significantly predict fixation count, several potential explanations may account for this outcome. Covert attention might play a more significant role in determining fixation count than overt disengagement (Carrasco et al., 2001). A participant who may appear to be disengaged (e.g., eyes not on the stimuli) could still be mentally attentive to the task. Conversely, the participant could be making several fixations without entirely engaging cognitively with the stimuli. This could imply that fixation count may reflect both overt and covert attention processes, which would dilute the predictive value of overt disengagement. Moreover, fixation count could be influenced by the overall task structure, visual complexity, and individual strategies that influence disengagement duration.

Also, it is important to note that if the eye tracker is not sensitive enough to detect subtle variations in gaze without concurrent video recording to interpret behaviors, the data may underestimate the relationship between disengagement and fixation count. Moreover, high data loss and missing samples could undermine the reliability of both disengagement and fixation parameters. Therefore, it could be possible that current eye-tracking technology may not be the most efficient tool to measure disengagement comprehensively, especially if covert processes may play a significant role.

VCI and FSIQ were also significant predictors of fixation count. Participants who had lower verbal comprehension index scores had greater fixation counts, suggesting that the children with lower verbal reasoning and comprehension abilities were able to identify the correct stimuli, but returned to them more often. Participants with lower VCI scores may rely more on visual and perceptual processing than on verbal reasoning, which may impact target processing strategies. Moreover, individuals with higher IQ scores had higher fixation counts with the target stimuli. Since higher IQ was also correlated with higher blink rates in children, the combination of these results suggests a relationship between verbal processing, overall intelligence, and visual attention regulation.

Overall, the results from the analyses suggested that there was no relationship between the different emotion categories presented in the trials and the blink rate during the single trials. Higher blink rates were not observed preceding overt disengagements for the children, as the blink rates were consistent across the two conditions. Though the findings did not support the hypotheses, there were still variables from the model that could be used to gain a deeper understanding of trial-by-trial engagement. There was an inverse relationship observed between *TFF* scores and fixation count, suggesting that slower *TFF* could be indicative of wandering attention or difficulties in maintaining focus.

The scores on the ECBI could reflect behavioral or emotional tendencies that affect trial engagement. Elevated ECBI scores may indicate externalizing behaviors, such as aggression or hyperactivity, which could reduce focus and hinder task completion (Bayley, 2005). Lower ECBI scores might suggest fewer behavioral barriers to engagement, potentially leading to greater sustained focus (Barkley, 2013; Achenbach, 2000). Similarly, lower verbal reasoning, as measured by the VCI (Verbal Comprehension Index), could impact trial engagement. While higher VCI scores are associated with greater reading comprehension and conceptual thinking, lower VCI scores are traditionally sought to reflect challenges in understanding verbal information, listening comprehension, and using language to reason and solve problems (Frijters et al, 2011). Individuals with lower VCI scores may still process task information through more visually driven techniques, allowing them to focus and engage with trial tasks more effectively. The child task did not have the emotion label matching component, as observed in the adult task, which may have benefited participants with low VCI. Based on the analysis, lower VCI participants may have been relying on more visual and perceptual processing than words, potentially highlighting the importance of nonverbal strength or adaptive strategies of individuals with lower verbal comprehension. Moreover, higher FSIQ scores are often associated with better cognitive flexibility and problem-solving abilities, which may translate to greater engagement in cognitively feasible tasks (Koriakin et al., 2013). In contrast, lower IQ scores might indicate challenges in comprehension, sustained attention, and task perseverance, potentially leading to disengagement (Sternberg, 2004).

Our hypothesis that changes in blink rate would precede an overt attentional disengagement was not supported. Participants showed similar blink rates across trials regardless of the emotion category of the stimulus and regardless of whether they overtly disengaged at any point during the trial. The lack of observed relationship between these variables may be due to several reasons, including the context of the study, individual variability, and the nature of blink dynamics. While blinks have a multifunctional nature as they provide eye lubrication and cognitive load management, it could be possible that not all blinks are indicative of disengagement, which would make it difficult to directly link blink rate to disengagement events. Spontaneous blinks may not always align with cognitive states related to disengagement, as some blinks may occur due to natural physiological patterns rather than attentional shifts. Since disengagement was operationally defined as the participant's gaze leaving the stimulus, which could also be exogenously cued (for example, from minor distractions in the room, despite the controlled experimental environment), it might not always coincide with endogenously generated changes in blink rate. Also, individual variability may skew the relationship between blink rate and disengagement events. Individuals' baseline blink rates may differ, as well as their attentional strategies, which could prevent establishing a generalizable relationship.

With regards to the current literature about spontaneous blink rate and dopamine, our findings challenge some of these notions. As mentioned previously, spontaneous blink rate is often utilized as a proxy for striatal dopamine functioning and some studies have linked higher dopamine activity to enhanced attention and cognitive functioning. Although our findings relate specifically to task-related blinking, they suggest that the blink rate may not solely predict attentional lapses. This could mean that the role of dopamine in disengagement may be more complex. Previous literature shows that spontaneous blink rate correlates with dopamine levels in resting state conditions, but task demands can affect this relationship (Zhang et al, 2023). Our findings suggest that spontaneous blink rate could reflect more baseline (tonic) dopamine levels than task-related blink rate and phasic dopamine bursts that are more related to disengagement events.

When analyzing the blink counts of the children during individual trials, we observed that some children have very high blink counts (e.g., 14 blinks over the 3 seconds of measurement). We posit that the children may be having a blink flurry or a rapid succession of blinks. In the literature, this phenomenon is indicative of increased cognitive load or decreased attention (Maffei et al., 2019). While these events were relatively rare in the data, and thus not appropriate for inclusion directly into blink counts for the previous models, including them in future models as a potential separate categorical predictor (e.g. presence of blink flurry) could provide valuable insight into the engagement of the children on an item level during the trials as well as determine their engagement during the presence of negatively valanced faces.

Limitations and Conclusions

Since the utilization of the eye-tracking system is not perfect, there may be the introduction of variables and factors that we have not anticipated, included in the data. Due to the lack of any visual recording during the child and caregiver tasks, we do not have exact information about what occurred during the trials. Therefore, when breaking down the single-trial data, it will be challenging to create assumptions about the exact behavior occurring during the task. However, we can mitigate some of this discrepancy by referring to the behavioral session notes taken during the tasks, which may aid in explaining any behavior that may affect the overall analysis. In the original behavioral analysis, there was a minimum data inclusion criterion, which we thought could have excluded the children who were possibly extremely disengaged and inattentive to the task. However, many of the files were usable regardless of this criterion, so this concern is no longer relevant.

One notable limitation in the study was the presence of missing data across several clinical and behavioral variables, most notably for ECBI scores. The level of missingness in this variable was beyond 30%, which exceeded the threshold where listwise deletion becomes unjustified and could introduce bias or reduce the overall statistical power. Considering these issues and aiming to maintain consistency when handling incomplete data, multiple imputation through R was employed rather than listwise deletion (Van Buuren et al, 2011). Through utilizing multiple imputation, we were able to preserve the sample size and reduce bias by estimating plausible values for the missing observations through predictive mean matching (PMM) (Sterne et al, 2009). Though this approach is statistically rigorous and widely accepted, the process relies on the assumption that the data loss is missing at random (MAR), which was largely the case, barring a few cases of missing ECBI scores due to clinical judgement regarding appropriateness for the measure over other similar measures. Considering that this dataset was not specifically designed for this study, and some scores, such as ECBI, were obtained from concurrent clinical records where clinical substitution can occur, future research should aim to minimize missing data through rigorous data collection protocols, minimizing record review.

The lack of relationship between time to first fixation (TFF) and disengagement duration (Fig. 5) serves as a notable limitation in this study. Although disengagement duration did not appear to predict TFF, the findings remain consistent within the constraints of the task. Considering the fixed 5-second trial duration, participants could disengage either before or after the initial fixation and still maintain a consistent average disengagement duration. As seen in Figure 5, most first fixations occurred within the first 2 seconds, while a majority of disengagement durations fell between 1 and 2.5 seconds. This pattern suggested that many participants disengaged after fixating on the target. These results aligned with prior work demonstrating that children are capable of rapidly disengaging after their initial fixation (De Haan et al., 2008), which further reduces the likelihood of a linear relationship between these variables. Moreover, by definition, disengagement requires participants to have first fixated on the screen, as it was operationalized as requiring a saccade away from the screen. Therefore, every disengagement event needed to be preceded by a period of on-screen fixation, regardless of whether that fixation was to the target. Disengagement after engagement with the target is also consistent with findings from Davies et al. 2018, who described search patterns in a subset of children with a history of ACEs who rapidly look away after first fixation on faces displaying negative emotions.

The present study aimed to investigate factors influencing trial engagement by assessing visual attention, cognitive abilities, behavioral tendencies, and physiological responses. The findings revealed that *Time to First Fixation* (TFF) and cognitive indices such as *Verbal Comprehension Index (VCI) and Full-Scale IQ (FSIQ)* were meaningful predictors of engagement, which suggested that participants with greater attention and cognitive efficiency strategies could sustain more attention during tasks. Conversely, behavioral measures like *ECBI* showed a weaker relationship with engagement, highlighting the complexity of these variables in predicting attentional states.

The lack of a significant relationship between blink rate and disengagement events suggests that blink rate may not serve as a direct indicator of attentional lapses. This could be due to the multifunctional nature of blinking, influenced by cognitive, emotional, and physiological factors that are beyond task-related disengagement. These findings offer valuable insights but also lead to important questions for future research. Future steps for this study should include the integration of more physiological and behavioral metrics, such as pupil dilation or saccade patterns, as well as video monitoring, to gain a more holistic view of engagement. Also, the role of individual differences, including emotional and cognitive profiles, should be included in future studies to understand individual engagement patterns. By addressing these gaps, future research can enhance our understanding of attention dynamics and contribute to the development of more accurate and reliable measures of sustained attention.

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