American Psychological Association

Neuropsychology

ISSN: 0894-4105

2020, Vol. 34, No. 6, 641–653
http://dx.doi.org/10.1037/neu0000636

A Diffusion Model Analysis of Sustained Attention in Children With Attention Deficit Hyperactivity Disorder

Cynthia Huang-Pollock
The Pennsylvania State University

Roger Ratcliff and Gail McKoon
Ohio State University

Alexandra Roule, Tyler Warner, Jason Feldman, and Shane Wise
The Pennsylvania State University

Objective: Whether children with attention deficit hyperactivity disorder (ADHD) have deficits in sustained attention remains unresolved due to the ongoing use of cognitive paradigms that are not optimized for studying vigilance and the fact that relatively few studies report performance over time. ***Method:*** In three independent samples of school-age children with (total $N = 128$) and without ADHD (total $N = 59$), we manipulated event rate, difficulty of discrimination, and use signal detection (SDT) and diffusion models (DM) to evaluate the cause of the vigilance decrement during a continuous performance task. ***Results:*** For both groups of children, a bias toward "no-go" over time (as indexed by the SDT parameter B'' and the DM parameter z/a) was responsible for generating the vigilance decrement. However, among children with ADHD, the rate at which information accumulated to make a no-go decision (vNoGo) also increased with time on task, representing a possible secondary mechanism that biases children against engagement. At all time points, children with ADHD demonstrated reduced sensitivity to discriminate targets from nontargets. ***Conclusion:*** Children with ADHD are particularly sensitive to the cost of task engagement, but nonspecific slower drift rate may ultimately provide a better conceptualization of the cognitive atypicalities commonly observed in that group. Results are interpreted in the context of updated conceptualizations of sustained attention and vigilance.

General Scientific Summary
Whether children with attention deficit hyperactivity disorder (ADHD) actually have difficulties sustaining their attention remains surprisingly unresolved. Using three different tasks designed to examine sustained attention, combined with a method of describing performance that utilizes both the speed and accuracy of responses, we found no evidence of a sustained attention deficit per se. However, we did find evidence that children with ADHD are more sensitive to the psychological costs of task engagement and are generally slower to accumulate information toward a decision.

Keywords: sustained attention, diffusion model, ADHD, event rate, difficulty

Supplemental materials: http://dx.doi.org/10.1037/neu0000636.supp

The vigilance decrement refers to a phenomenon in which the probability of detecting an infrequent signal decreases with time on task. It is an incredibly robust effect that has been observed in the laboratory as well as in real-world scenarios including radio operators detecting enemy aircraft, radiologists reviewing films for cancer, quality control inspectors searching for defects, and airline security screeners looking for contraband (Evans, Birdwell, & Wolfe, 2013; Mackworth, 1948; Meuter & Lacherez, 2016). Innumerable variations exist among laboratory paradigms designed to invoke this decrement. However, at their core, such tasks (known as continuous performance tasks, or CPTs) require observers to detect a rare target among nontargets over the course of 10–30 min

This article was published Online First April 23, 2020.
Cynthia Huang-Pollock, Department of Psychology, The Pennsylvania State University; Roger Ratcliff and Gail McKoon, Department of Psychology, Ohio State University; Alexandra Roule, Tyler Warner, Jason Feldman, and Shane Wise, Department of Psychology, The Pennsylvania State University.
This work was supported in part by National Institute of Mental Health Grant R01 MH084947 to Cynthia Huang-Pollock. The modeling was supported by NIA R01-AG041176 to Roger Ratcliff. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institute of Mental Health or the National Institutes of Health.
Correspondence concerning this article should be addressed to Cynthia Huang-Pollock, Department of Psychology, The Pennsylvania State University, 130 Moore Building, University Park, PA 16802. E-mail: CLH39@psu.edu

or more (for reviews, see Huang-Pollock, Karalunas, Tam, & Moore, 2012; Riccio, Reynolds, Lowe, & Moore, 2002).

The mechanisms most commonly invoked to measure the vigilance decrement derive from signal detection theory (SDT), a theoretical framework used to measure the success or failure of discrimination decisions. The two parameters used to describe performance are sensitivity and bias. Sensitivity refers to the ability to detect signals from noise. The more distinct signals are from noise, the easier it is for an individual to differentiate between them. Sensitivity is a function of the signal (i.e., more difficult discriminations lead to lower sensitivity estimates) as well as trait of the individual (i.e., some people are better perceivers than others). A' is a commonly used nonparametric index of sensitivity and ranges from 0.5 (chance performance) to 1.0 (perfect performance; Stanislaw & Todorov, 1999).

In contrast, bias refers to an individual's tendency to respond in a particular manner (e.g., a tendency to respond "yes, target present" or "no, target absent"). Bias is based on internal decision rules that can be influenced by a complex interaction of task instructions, payoff ratios, proportion manipulations, and an individual's own proclivity to respond "yes" or "no" (Sarter, Givens, & Bruno, 2001; See, Warm, Dember, & Howe, 1997; Witt, Taylor, Sugovic, & Wixted, 2015). B'' is a common nonparametric index of bias that ranges from -1 (bias in favor of a "target present" response) to 1 (bias in favor of "target absent" response), with 0 indicating no bias (Stanislaw & Todorov, 1999). Calculation of both sensitivity and bias utilize only the hit and false alarm rates (the speed of the response is irrelevant). Therefore, the presence of errors is essential; the parameters are much less reliably interpreted when accuracy is high or if performance is perfect (Sarter et al., 2001), which is unfortunately the case for many CPT tasks used in both research and clinical practice.

Although SDT parameters are invoked with such frequency to have become almost synonymous with the concept of sustained attention, SDT is not the only theoretical framework that could be brought to bear in the study of vigilance. Like SDT, the diffusion model (DM) is a model of decision-making, but it differs from SDT in that it explicitly models processes that are believed to influence the accuracy *as well as* speed of a decision. Because the DM addresses speed of processing, it may be able to provide insights into the causes of the vigilance decrement that are invisible to SDT. After a stimulus is encoded, the DM assumes that a noisy information accumulation process occurs in which evidence for or against one or the other option accrues until it reaches the associated boundary, at which point a response is initiated. Reaction times are understood as the sum of the time it takes for information to reach the boundary (i.e., decision time) plus the amount of time needed to complete all nondecisional processes (e.g., encoding of the stimulus and preparation/execution of the motor response, referred to as T_{er}). The primary processes that influence decisional time are (a) the rate at which information accumulates (called drift rate, and denoted as v), (b) the start point of the decisional process (denoted as z), and (c) the degree to which speed versus accuracy is being emphasized (called boundary separation, denoted as a).

Drift rate can be considered a measure of sensitivity (like A' in SDT) and is similarly a function of both the stimulus (more difficult discriminations lead to slower drift rates) and the perceiver (i.e., there are individual differences in drift rate; Ratcliff, 1978; Wagenmakers, van der Maas, & Grasman, 2007). The position of the starting point (z) of the decisional process relative to the two boundaries represents how much evidence needs to be sampled or accumulated for each response option. Because the start point can only be interpreted relative to the boundary separation, z/a is often used to represent the relative bias (Voss, Nagler, & Lerche, 2013). Regardless, both z and z/a reflect response expectancy biases and are most commonly and easily influenced when response proportions are manipulated or particular responses are differentially rewarded (Leite & Ratcliff, 2011; Mulder, Wagenmakers, Ratcliff, Boekel, & Forstmann, 2012; Ratcliff, 1985; White & Poldrack, 2014). For example, consider a numerosity discrimination task, in which participants are asked whether a given stimulus contains "many" or "few" asterisks. A 75:25 ratio of many:few trials would shift the start point of the decision process away from the center and closer to (or bias toward) the "many" boundary. In this way, response proportion manipulation effects on start point are very similar to their effects on B'' in SDT. A second way of modeling bias in the diffusion model is through changes in the zero point of the drift rate (Ratcliff, 1985; Ratcliff & McKoon, 2008). When this occurs, the drift rate to one decisional boundary is faster and the drift rate toward the other is slower (e.g., drift rate to "many" is faster than drift rate to "few").

Boundary separation (a) reflects both experimental instructions to emphasize speed over accuracy (or vice versa) as well as an individual's own speed–accuracy trade-off settings. Instructions to emphasize accuracy of response lead to wider boundaries; instructions to emphasize the speed of response lead to narrower boundaries. Individual differences in all model parameters have been observed (Ratcliff, Thapar, & McKoon, 2010, 2011).

The ability to sustain attention is critical to the success of a range of daily activities, and problems with attention are ubiquitous across a range of mental health conditions, most notably childhood attention deficit hyperactivity disorder (ADHD). Understanding the mechanism of performance decline is needed to develop interventions or accommodations to reduce its decline. To date, the preponderance of evidence derived from SDT parameters is that among healthy adult observers, the vigilance decrement is caused by observers biasing their responses over time to match the (low) signal base rate of the task at hand (Parasuraman, 1979; Thomson, Besner, & Smilek, 2016). Thus, adding "decoys" to the work flow for standard medical screenings, or for baggage screeners at airports, should (and has been shown to) improve signal detection for these low-prevalence conditions or situations (Evans et al., 2013; Methot & Huitema, 1998).

Examination of the mechanisms driving the vigilance decrement among children is rarer and previously has not been undertaken from a DM perspective. Two large meta-analytic reviews spanning the sustained attention literature between 1973 and 2010 found replicated evidence of reduced sensitivity to detect targets from nontargets among children with ADHD but no group differences in bias (Huang-Pollock et al., 2012; Losier, McGrath, & Klein, 1996). ADHD-related effect sizes for time-on-task effects (i.e., the core of the sustained attention construct) were small to moderate (Huang-Pollock et al., 2012). However, the empirical work on which those reviews were based used paradigms that produced very few errors, which makes the interpretation of SDT parameters much less reliable. Furthermore, the number of studies reporting time-on-task effects was quite limited ($k = 4$–7), and due to the lack of trial-by-trial data, DM parameters were estimated using the EZ diffusion model (Wagenmakers et al., 2007). The EZ model estimates the parameters of interest by transforming mean reaction time (RT), RT variance, and accuracy for each condition of the experiment separately. Based on this transformation, the model cannot easily be falsified. Therefore, despite the fact that identifying the mechanisms responsible for sustaining attention are key components of influential theories of ADHD, the very question of whether a sustained attention deficit exists in ADHD remains unresolved.

In the current study, we examined the cognitive causes of the vigilance decrement among children with and without ADHD, using a diffusion model approach that takes full advantage of both error rates and speeds of responses. Importantly, changes in bias are relatively easy to observe and are commonly manipulated via verbal instructions (e.g., "most of the stimuli will not be targets"), differential payoffs (e.g., greater rewards for some responses over others), or stimulus ratios (e.g., most of the stimuli require a "yes" response). However, changes in sensitivity over time are more difficult to obtain and are commonly only observed with fast event rates and when discrimination decisions are more difficult (Koelega, Brinkman, Hendriks, & Verbaten, 1989; Methot & Huitema, 1998). In the following two experiments, we manipulated event rate and difficulty of the discrimination decision to increase the probability of detecting a sensitivity decrement if it exists.

We hypothesized a main effect of block, representing the standard vigilance decrement in which performance deteriorates over time; a main effect of diagnostic status in which children with ADHD will underperform their non-ADHD same-aged peers; and a main effect of task in which more difficult discriminations and faster event rates will reduce the sensitivity to discriminate between targets and noise (i.e., A' and v). Based on preexisting literature, we anticipated a main effect of block on bias (B'' and z/a), suggesting that changes in bias drive the vigilance decrement. Because changes in sensitivity are more difficult to detect, we anticipated a Task × Block interaction for indices of sensitivity (i.e., A', v) in which sensitivity would decline with time on task when discrimination decisions are more difficult and when event rate is faster. There was no expectation that these manipulations would have an influence on bias measures. Two- and three-way interactions with ADHD would suggest the presence of ADHD-related deficits in sustained attention and/or diagnosis-related mechanisms of that deficit.

Method

Participants

Following long-recognized best-practice recruitment guidelines for clinical research (Berkson, 1946; Cohen & Cohen, 1984; Goodman et al., 1997; Grobbee & Hoes, 2015), children aged 8–12 were exclusively recruited from the community. They were recruited from radio, magazine, and Internet ads and posted public flyers. Flyers were also provided to local schools in the Central and Dauphin counties of Pennsylvania. Exclusion criteria included (a) current nonstimulant medication treatment (e.g., neuroleptics or antidepressants); (b) diagnosis of pervasive developmental disorder, intellectual disability, sensorimotor disability, psychosis, or other parent-reported neurological disorder; and (c) estimated Full Scale IQ (FSIQ) < 80. Common childhood disorders, such as anxiety, depression, oppositional defiant disorder, and conduct disorder, were assessed using the Diagnostic Interview Schedule for Children (DISC; 4th ed.; Shaffer, Fisher, & Lucas, 1997) and behavioral rating scales but were not exclusionary. Table 1 provides sample demographics.

Children with ADHD. Children with ADHD met *Diagnostic and Statistical Manual of Mental Disorders* (*DSM*; 5th ed.) criteria for ADHD including age of onset, duration, cross-situational severity, and impairment as determined by parent report on the DISC. To demonstrate cross situational severity, at least one parent *and* one teacher report of behavior on the attention, hyperactivity, or ADHD subscales of the Behavioral Assessment Scale for Children-2 (Reynolds & Kamphaus, 1992) or the Conner's Rating Scale (Conners, 1997) was required to exceed the 85th percentile (T score > 61). Both measures are commonly used and well validated for the evaluation and diagnosis of ADHD. Following *DSM–IV* field trials (Lahey et al., 1994), an "or" algorithm inte-

Table 1
Sample Demographics

Variables	Slow/easy		Fast/easy		Slow/hard	
	Control	ADHD	Control	ADHD	Control	ADHD
n	20 (13 girls)	45 (14 girls)	19 (11 girls)	63 (23 girls)	20 (8 girls)	20 (6 girls)
FSIQ	105.90 (6.89)	105.36 (11.34)	103.37 (8.17)	100.57 (12.24)	102.25 (8.31)	107.80 (17.38)
Age (years)	10.08 (1.12)	10.33 (1.15)	9.47 (1.32)	9.98 (1.29)	10.06 (0.98)	9.37 (1.15)
#AttnSxs	0.35 (0.49)	8.07 (0.86)	0.42 (0.61)	7.86 (1.77)	0.40 (0.60)	7.95 (1.76)
#HyperSxs	0.30 (0.57)	5.71 (2.68)	0.21 (0.54)	5.68 (2.70)	0.20 (0.41)	5.35 (3.15)
PBASCHyper	43.20 (5.86)	63.64 (11.83)	39.68 (3.96)	68.56 (14.34)	41.70 (4.14)	63.40 (14.41)
PBASCAttn	43.60 (7.10)	65.33 (6.97)	41.32 (6.59)	67.11 (7.82)	40.70 (6.38)	63.90 (8.80)
TBASCHyper	42.90 (2.71)	59.89 (13.01)	43.00 (2.36)	59.34 (11.60)	44.00 (3.89)	59.65 (12.61)
TBASCAttn	42.25 (4.64)	61.69 (6.72)	44.95 (5.37)	61.50 (7.22)	42.90 (5.77)	64.10 (6.21)
#ODD/CD	1	28	1	30	0	12
#MDD/DD	0	5	0	5	0	4
#GAD	0	7	0	5	0	2

Note. Values are means with standard deviations in parentheses. BASC reported in t-scores. ADHD = attention deficit hyperactivity disorder; FSIQ = Full Scale IQ; P = parent rating; T = teacher rating.

grating parent report on the DISC and teacher report on the ADHD Rating Scale (DuPaul, Power, Anastopoulos, & Reid, 1998) was used to determine final symptom count. Children prescribed stimulant medication were asked to discontinue medication use for 24–48 hr.

Non-ADHD controls. Controls did not meet ADHD criteria on DISC, had *T* scores below the 80th percentile (*T* score < 58) on all ADHD-related parent and teacher rating scales, and had never been previously diagnosed or treated for ADHD. All had ≤ 4 total symptoms and ≤ 3 symptoms per ADHD dimension according to the "or" algorithm. The presence of anxiety, depression, oppositional defiant, and conduct disorders were not exclusionary. To control for the potential confounding effects of IQ on the high end of the spectrum, controls were required to have estimated IQs $<$ 115. No upper IQ limit was set for children with ADHD.

Validation and comparison of samples in each condition. Cohorts of children with and without ADHD were recruited consecutively to complete one of three CPT versions. In the slow event rate/easy discrimination task ("basic"), there were $n = 45$ children with ADHD (14 girls) and $n = 20$ non-ADHD (13 girls) controls. Sample ethnicity reflected regional demographics: 84.6% Caucasian, 7.7% African American, 1.5% Asian, and 6.2% mixed ethnicity. Sixteen (36%) children with ADHD were prescribed a stimulant medication, and the median medication washout period was 75 hr.

In the fast event rate/easy discrimination task, there were $n = 63$ children with ADHD (23 girls) and $n = 19$ non-ADHD controls (11 girls). Sample ethnicity was 65.4% Caucasian, 9.9% African American, 16% Hispanic, 1.2% Asian, and 7.4% mixed ethnicity. Nineteen (82%) children with ADHD were prescribed a stimulant medication, and the median medication washout period was 64 hr.

In the slow event rate/hard discrimination task, there were $n = 20$ children with ADHD (six girls) and $n = 20$ non-ADHD controls (eight girls). Sample ethnicity was 65% Caucasian, 2.5% African American, 17.5% Hispanic, 2.5% Asian, and 12.5% mixed ethnicity. Seven (35%) children with ADHD were prescribed a stimulant medication, and the median medication washout period was 41 hr.

Within each of the three conditions, parent and teacher ratings of ADHD symptomology for the ADHD group exceeded controls (all $p < .001$). There were no diagnostic differences in age (all $p >$ .05) or IQ (obtained using a two-subtest short form [vocabulary and matrix reasoning] of the Wechsler Intelligence Scale for Children-IV; Wechsler, 2003; all $p > .21$). Compared to the $n =$ 86 children with ADHD who had not taken a prescription medication to treat ADHD within the last 30 days (though they may have in the past), children who were currently prescribed medications were slightly older (10.33 years vs. 9.82 years), $F(1, 126) = 4.88$, $p = .03$, but did not differ in symptom severity or FSIQ (all $p > .10$; see online supplemental materials for additional analyses by medication usage).

Procedure

Informed written consent from parents and verbal assent from children were obtained prior to participation. Parents were given $100 and relevant clinical feedback. Children were given a small prize. Participants completed the paradigms described next as part of a battery of tasks associated with a larger study examining neurocognitive deficits in childhood ADHD. All children completed the tasks within the battery in the same order.

The Continuous Performance Task paradigm used stimuli from a numerosity discrimination task (Ratcliff, Love, Thompson, & Opfer, 2012). A total of 800 trials were administered, with optional rest periods provided after each set of 80 trials. All children completed all trials of the task.

At the start of each trial, white asterisks filled random positions in a 10×10 array at the center of a black screen. Children were told

> We're going to play a game called the Candy Factory now. Some of the boxes of candy that the factory makes have a lot of candy in them, and some only have a little. But the sorter is broken! We need your help! Every time you see a box that has "a lot" of candy, press the spacebar. Don't press anything if the box has "a little" bit of candy. This is a hard game, but try to work as quickly as you can without making mistakes. Let's try some for practice.

Four practice trials were then presented as examples. Additional practice following those trials was available if necessary to clarify instructions, but instructions were simple enough that this was rarely necessary. For all tasks, 25% of the stimuli (selected at random without replacement) had $>$50 asterisks (i.e., "a lot" of candy) and were "go" trials. The remaining 75% had $<$50 asterisks (i.e., "a little bit" of candy) and were "no-go" trials. Children were never told of the explicit sorting rule, but a brief tone on errors was provided.

In the slow event rate/easy discrimination task (basic), boxes contained between 31 and 40 asterisks (no-go) or 61–70 asterisks (go). Stimuli remained onscreen for 1,500 ms, even if a response was made within that time period. The next trial began with a 300-ms blank screen, after which another box would appear. Total time to completion was ~24 min.

In the fast event rate/easy discrimination condition, boxes contained between 31 and 40 asterisks (no-go) or 61–70 asterisks (go). Participants were given up to 1,500 ms to respond, but if they responded before that time limit, the next trial began immediately. This manipulation produces a phenomenological experience of a time pressure. Total time to completion was ~21 min.

In the slow event rate/difficult discrimination task, boxes contained between 36 and 45 asterisks or 56–65 asterisks. Thus, difficulty was increased by decreasing the distance between the presented stimuli and the criterion of 50. Stimuli remained onscreen for 1,500 ms, even if a response was made within that time period. The next trial then started with a 300-ms blank screen, after which another box would appear. Total time to completion was ~24 min. The probability of detecting changes in sensitivity (i.e., A') over time increases when there are at least 24 events per minute (Parasuraman, 1979; Parasuraman & Davies, 1977; Thomson et al., 2016). Event rates were sufficiently frequent in both the slow event rate conditions (at 33 events per minute), as well as the fast event rate condition (37 events per minute) to detect declines in sensitivity if present.

Data Analytic Approach

Calculating signal detection theory parameters. To compute both the SDT and diffusion model parameters, the 800 trials were divided into two blocks of trials (i.e., first and last half). This provided enough trials for each set of parameters to be calculated. We used nonparametric measures of sensitivity (A') and bias (B'') calculated as reported in Stanislaw and Todorov (1999). SDT parameters cannot be calculated in the absence of errors, which explains the slightly reduced *n*s (and *df*s) used for those comparisons. A total of $n = 6$ non-ADHD controls (10% of sample) and $n = 14$ children with ADHD (11% of sample) were removed from SDT analyses because of perfect performance.

Fitting the diffusion model. Following convention, RTs < 300 ms were removed from the data (Ratcliff et al., 2012). The values of all parameters were estimated simultaneously for all the data for each participant individually (see Ratcliff, Huang-Pollock, & McKoon, 2018; Ratcliff & Tuerlinckx, 2002 for full details). To fit the model to the data, RT distributions for all go responses (i.e., correct go as well as failed inhibits) were represented by nine quantiles, the .1, .2, .3, . . . , .9 quantiles. The quantiles and the response proportions were entered into a chi-square minimization routine (Ratcliff & Tuerlinckx, 2002), and the diffusion model was used to generate the predicted cumulative probability of a response occurring by that quantile RT. Subtracting the cumulative probabilities for each successive quantile from the next higher quantile gives the proportion of responses between adjacent quantiles. For a chi-square computation, these are the expected proportions, to be compared to the observed proportions of responses between the quantiles (i.e., the proportions between 0, .1, .2, . . . , .9, and 1.0, which are .1, .1, .1, . . . , and .1). The proportions are multiplied by the number of observations in the condition (this produces values of the proportions weighted by accuracy) to give observed (O) and expected (E) frequencies. Summing over $(O-E)^2/E$ for all conditions gives a single chi-square value to be minimized. The number of degrees of freedom in the data are the 20 proportions between and outside the quantiles (10 each for correct and error responses) minus 1 (because the sum must equal 1) multiplied by the number of conditions in the data. For all no-go responses (i.e., correct no-go responses and errors of omission, where the child did not go when a go response should have been made), a single bin was used for the contribution to chi square—namely, $(O-E)^2/E$, where O is the observed frequency of no-go responses and E is the expected frequency of no-go responses. Thus, the number of degrees of freedom was 10–1 for the RT bins for the go responses plus 1 for the no-go responses.

We note that the within trial variance of the diffusion process for any given trial is usually treated as a scaling parameter (by convention, it is typically set to 0.1; see Wagenmakers et al., 2007). If this were doubled, then other parameters in the model would also be doubled, but the predicted values would be identical. Thus, interpretation of these values is dependent on the relative values. Larger absolute values of drift rate indicate faster drift. Larger values of boundary separation indicate more conservative responding. *z/a* is the relative distance between the start point and no-go boundary, where 0.50 indicates no bias, and smaller values indicate a bias toward no-go. T_{er} is reported in seconds.

Results

Figure 1 illustrates main effects and interactions for primary variables by ADHD status and block and across event rate and difficulty manipulations. A summary of performance data is provided in Table 2. Analyses performed using dimensional symptom count, either as a whole or with each of the inattentive and hyperactive/impulsive domains separately, mirrored those of between-group analyses and provided no new information (see online supplemental materials for correlation table). Only the between-groups analyses are presented below in the text. Similarly, violations of the homogeneity of variance assumption can be problematic when groups are unbalanced as they were in the current study (Blanca, Alarcón, Arnau, Bono, & Bendayan, 2017). Levene's test was examined in all analyses and was nonsignificant for most dependent variables. Where the homogeneity assumption was violated, analyses were reexamined using Welch, Brown-Forsythe, and Kruskal-Wallis tests that do not assume homogeneity of variance. Results remained the same to those reported next.

Event Rate Manipulation

Table 3 provides *F*, *p*, η_p^2, and statistics for all comparisons. Performance in the slow event rate/easy discrimination paradigm (basic) was compared against the fast event rate/easy discrimination paradigm. Repeated measures multivariate analysis of variance (MANOVA) was first conducted on the 11 dependent variables (RT, Standard deviation of reaction time (SDRT), omissions, commissions, A', B'', *a*, T_{er}, *v*Go, *v*NoGo, *z/a*). Statistically significant main effects or interactions were then analyzed in a series of 2 (Block: first vs. last half of trials) × 2 (Task: slow vs. fast) × 2 (Diagnosis: ADHD vs. control) mixed between- and within-subjects ANOVAs reported next. The three-way Block × Task × ADHD interaction was not statistically significant for any dependent variable (effect sizes ranging from $\eta_p^2 < 0.000$ to $\eta_p^2 = 0.026$) and had limited theoretical significance. Therefore, it was removed from the generalized linear model (GLM).

Standard task variables. There was a main effect of event rate in which RT was shorter and the number of commissions was higher for the fast event rate paradigm (both $p < .001$, $\eta_p^2 > 0.06$). The standard vigilance decrement was also seen (i.e., main effect of block) in which RTs became longer, the number of omissions increased, and the number of commissions decreased with time on task (all $p < .001$, $\eta_p^2 > 0.09$). Additionally, there was a main effect of diagnosis in which children with ADHD performed more poorly than non-ADHD controls. The Block × ADHD interaction was not significant for any of these standard outcome variables (i.e., RT, SDRT, errors; all $p > .16$, $\eta_p^2 < 0.01$). This lack of interaction is consistent with previous meta-analytic reviews that have not found strong evidence of a sustained attention deficit among children with ADHD. The Block × Event Rate interaction was also not significant for any variable (all $p > .11$, $\eta_p^2 < 0.02$), suggesting that manipulation of event rate did not moderate the size of the vigilance decrement.

Model-based task variables. Using SDT and DM parameters to decompose these effects, we found the vigilance decrement was driven by changes in bias. There was a main effect of block in which B'' shifted toward "no, target absent," and the relative start point of the decision process (*z/a*) moved closer to the no-go boundary with time on task, block effect for B'': $F(1, 124) = 48.65$, $p < .001$, $\eta_p^2 = 0.28$, where mean and standard error of Block 1 $B'' = 0.17$ (0.04) and Block 2 $B'' = 0.46$ (0.03); block effect for *z/a*: $F(1, 144) = 18.74$, $p < .001$, $\eta_p^2 = 0.12$, where mean and standard error of Block 1 $z/a = 0.54$ (0.01) and Block 2 $z/a = 0.48$

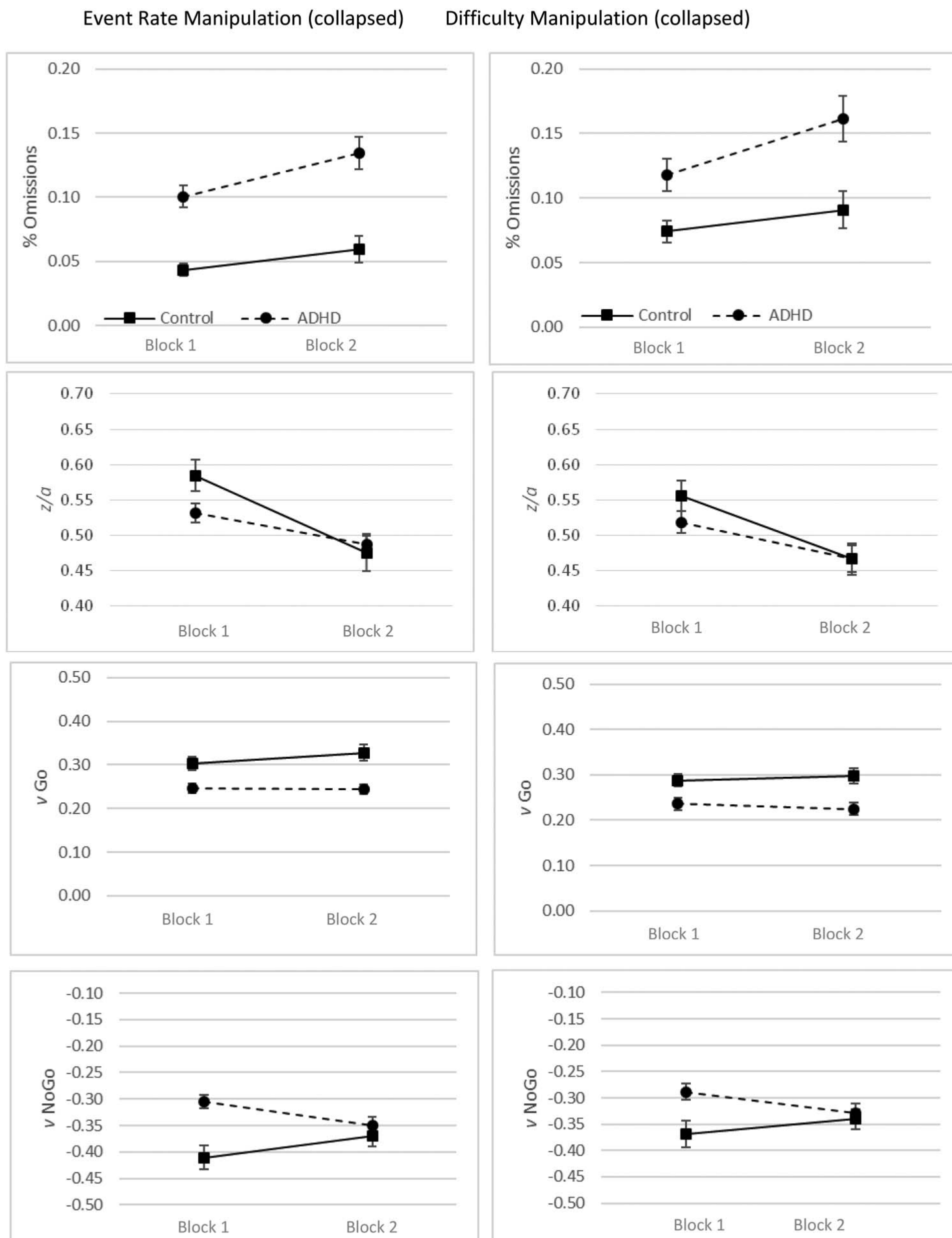

Figure 1. Performance over time by diagnosis for % omissions, relative start point (*z/a*), drift rate (*v*) to go decisions, and drift rate (*v*) to no-go decisions. Larger absolute values of *v* represent faster drift. Smaller values of *z/a* are closer to the no-go boundary. Left column: event rate manipulation (collapsed). Right column: difficulty manipulation (collapsed). ADHD = attention deficit hyperactivity disorder; vGo = drift rate to Go decision; vNoGo = drift rate to No Go decision; z/a = relative distance between the start point and no-go boundary.

(0.01). This was not the case for sensitivity, despite the fact that both paradigms had sufficiently frequent, successive, and dimensional stimuli, which by historical taxonomy should have produced a change in sensitivity if it were present; i.e., block effect for A', *v*Go, and *v*NoGo: all $p > .31$, $\eta_p^2 < 0.01$. However, when event rate was faster, T_{er} was shorter and B'' was less biased to no-go, event rate for T_{er}: $F(1, 144) = 19.53$, $p < .001$, $\eta_p^2 = 0.12$; B'': $F(1, 124) = 33.58$, $p < .001$, $\eta_p^2 = 0.21$.

Consistent with previous meta-analytic findings, poor performance among children with ADHD was driven by reduced sensitivity to distinguish targets from nontargets (diagnosis effect for A', *v*Go, *v*NoGo: all $p < .01$, $\eta_p^2 > 0.05$), but there were no group differences in bias (diagnosis effect for B'' and *z*: both $p > .30$, $\eta_p^2 < 0.01$). A significant Block × ADHD interaction for *v*NoGo, $F(1, 144) = 7.92$, $p = 0.006$, $\eta_p^2 = 0.05$, was also found. Here, *v* to NoGo sped up with time on task for

Table 2
Summary of Performance Data

Variable	CPT	Control Blocks 1–5	Control Blocks 6–10	Control *n*	ADHD Blocks 1–5	ADHD Blocks 6–10	ADHD *n*
% Acc	1	77.76 (0.29)	77.73 (0.44)	20	75.11 (0.82)	75.56 (0.75)	45
	2	75.83 (0.75)	77.40 (0.53)	19	71.15 (1.14)	72.77 (1.12)	63
	3	68.82 (1.81)	72.25 (1.61)	20	66.14 (1.50)	68.47 (1.42)	20
RT (ms)	1	748.13 (16.87)	810.27 (24.30)	20	792.93 (15.61)	834.35 (20.09)	45
	2	662.12 (19.92)	705.20 (22.94)	19	706.54 (13.73)	735.88 (14.84)	63
	3	715.99 (16.99)	753.25 (21.79)	20	779.82 (17.17)	791.76 (19.81)	20
SDRT (ms)	1	180.17 (8.41)	185.19 (9.25)	20	220.28 (8.33)	217.21 (8.06)	45
	2	175.01 (11.44)	171.63 (11.21)	19	229.37 (6.22)	232.33 (6.26)	63
	3	202.81 (11.29)	203.32 (10.72)	20	236.14 (9.19)	244.31 (9.62)	20
% Commissions	1	0.02 (0.00)	0.02 (0.00)	20	0.05 (0.01)	0.03 (0.01)	45
	2	0.06 (0.01)	0.03 (0.01)	19	0.11 (0.02)	0.08 (0.02)	63
	3	0.15 (0.03)	0.09 (0.03)	20	0.17 (0.02)	0.12 (0.02)	20
% Omissions	1	0.05 (0.01)	0.07 (0.01)	20	0.09 (0.01)	0.14 (0.02)	45
	2	0.04 (0.01)	0.05 (0.02)	19	0.11 (0.01)	0.13 (0.02)	63
	3	0.10 (0.01)	0.12 (0.03)	20	0.18 (0.03)	0.22 (0.04)	20
A'	1	0.98 (0.00)	0.98 (0.00)	18	0.95 (0.01)	0.95 (0.01)	38
	2	0.97 (0.00)	0.98 (0.01)	15	0.93 (0.01)	0.93 (0.01)	56
	3	0.93 (0.01)	0.94 (0.01)	20	0.89 (0.02)	0.89 (0.02)	20
B''	1	0.39 (0.08)	0.52 (0.08)	18	0.35 (0.05)	0.65 (0.04)	38
	2	−0.08 (0.09)	0.32 (0.09)	15	0.05 (0.05)	0.35 (0.05)	56
	3	−0.06 (0.09)	0.11 (0.11)	20	−0.02 (0.07)	0.19 (0.09)	20
a	1	0.22 (0.01)	0.19 (0.01)	20	0.20 (0.01)	0.20 (0.01)	45
	2	0.18 (0.01)	0.19 (0.01)	19	0.19 (0.01)	0.20 (0.01)	63
	3	0.16 (0.01)	0.17 (0.01)	20	0.17 (0.01)	0.17 (0.01)	20
T_{er}	1	0.46 (0.02)	0.48 (0.03)	20	0.44 (0.01)	0.46 (0.01)	45
	2	0.42 (0.01)	0.41 (0.01)	19	0.39 (0.01)	0.41 (0.01)	63
	3	0.45 (0.01)	0.46 (0.02)	20	0.46 (0.01)	0.45 (0.02)	20
*v*Go	1	0.31 (0.02)	0.31 (0.02)	20	0.25 (0.02)	0.24 (0.02)	45
	2	0.30 (0.02)	0.35 (0.03)	19	0.24 (0.01)	0.24 (0.01)	63
	3	0.27 (0.02)	0.29 (0.02)	20	0.20 (0.02)	0.18 (0.02)	20
*v*NoGo	1	−0.45 (0.02)	−0.36 (0.03)	20	−0.33 (0.02)	−0.36 (0.02)	45
	2	−0.36 (0.03)	−0.38 (0.03)	19	−0.29 (0.02)	−0.34 (0.02)	63
	3	−0.28 (0.04)	−0.33 (0.03)	20	−0.19 (0.02)	−0.25 (0.03)	20
z/a	1	0.58 (0.03)	0.46 (0.04)	20	0.52 (0.02)	0.46 (0.02)	45
	2	0.59 (0.03)	0.49 (0.03)	19	0.54 (0.02)	0.51 (0.02)	63
	3	0.53 (0.03)	0.48 (0.03)	20	0.52 (0.03)	0.48 (0.03)	20

Note. Values are means with standard errors in parentheses. ADHD = attention deficit hyperactivity disorder; SDRT = standard deviation of reaction time; a = boundary separation; Ter = non-decision time; vGo = drift rate to Go decision; vNoGo = drift rate to No Go decision; z/a = relative distance between the start point and no-go boundary; CPT = continuous performance task; RT = reaction time. CPT type: 1 = slow/easy, 2 = fast/easy, 3 = slow/hard.

children with ADHD, $F(1, 106) = 8.44$, $p = .004$, $\eta_p^2 = 0.07$; mean and standard error Block 1 = −0.30 (0.01), Block 2 = −0.35 (0.01). However, there was no effect of block for controls; if anything, the effect was in the opposite direction, $F(1, 37) = 2.50$, $p = .12$, $\eta_p^2 = 0.06$; mean and standard error Block 1 = −0.41 (0.02), Block 2 = −0.37 (0.02). Thus, at least two mechanisms are driving the vigilance decrement. The first mechanism, observed in both children with and without ADHD, is changes in bias with time on task. The second mechanism, observed only among children with ADHD, is that drift rate to no-go decisions speed up.

Difficulty Manipulation

Table 4 provides *F*, *p*, η_p^2, and statistics for all comparisons. Performance on the slow event rate/easy discrimination paradigm (basic) was compared against the slow event rate/difficult ("difficult") discrimination paradigm. Repeated measures MANOVA was first conducted on the 11 dependent variables (RT, SDRT, omissions, commissions, A', B'', *a*, T_{er}, *v*Go, *v*NoGo, *z/a*). Statistically significant main effects or interactions were then analyzed in a series of 2 (Block: first vs. last half) × 2 (Task: easy vs. hard) × 2 (Diagnosis: ADHD vs. control) mixed between- and within-subjects ANOVAs reported next. The Block × Task × ADHD interaction was not statistically significant for any dependent variable (effect sizes ranging from $\eta_p^2 < 0.000$ to $\eta_p^2 = 0.036$) and had limited theoretical significance. Therefore, it was removed from the GLM.

Standard task variables. There was a main effect of difficulty in which the number of commissions and omissions were higher, and SDRT larger, for the difficult paradigm (all $p < .02$, $\eta_p^2 > 0.05$). The standard vigilance decrement was also seen (main effect of block) in which the number of omissions increased, commissions decreased, and RTs became longer with time on task (all $p < .001$, $\eta_p^2 > 0.13$). Also as expected, there was a main effect

Table 3
Table of Statistics for Event Rate Manipulation

	F	*p*	η_p^2	*df*
Within-subject factors				
Block				
RT	42.71	<.001	0.23	1,144
SDRT	0.03	.86	<.001	1,144
Commissions	13.90	<.001	0.09	1,144
Omissions	14.62	<.001	0.09	1,144
A'	0.05	.82	<.001	1,124
B''	48.65	<.001	0.28	1,124
a	0.20	.66	<.001	1,144
T_{er}	1.12	.29	0.01	1,144
*v*Go	1.04	.31	0.01	1,144
*v*NoGo	0.00	1.00	<.001	1,144
z/a	18.74	<.001	0.12	1,144
Block × ADHD				
RT	1.61	.21	0.01	1,144
SDRT	0.01	.92	<.001	1,144
Commissions	0.72	.40	<.001	1,144
Omissions	2.03	.16	0.01	1,144
A'	0.23	.63	<.001	1,124
B''	0.25	.62	<.001	1,124
a	1.25	.27	0.01	1,144
T_{er}	0.18	.67	<.001	1,144
*v*Go	2.14	.15	0.01	1,144
*v*NoGo	7.92	.01	0.05	1,144
z/a	3.07	.08	0.02	1,144
Block × Event Rate				
RT	1.35	.25	0.01	1,144
SDRT	0.12	.73	<.001	1,144
Commissions	2.56	.11	0.02	1,144
Omissions	0.85	.36	0.01	1,144
A'	1.57	.21	0.01	1,124
B''	0.96	.33	0.01	1,124
a	1.12	.29	0.01	1,144
T_{er}	0.10	.76	<.001	1,144
*v*Go	1.08	.30	0.01	1,144
*v*NoGo	3.37	.07	0.02	1,144
z/a	0.74	.39	0.005	1,144
Between-subject factors				
ADHD				
RT	3.38	.07	0.02	1,144
SDRT	29.02	<.001	0.17	1,144
Commissions	4.97	.03	0.03	1,144
Omissions	14.16	<.001	0.09	1,144
A'	7.66	.01	0.06	1,124
B''	1.09	.30	0.01	1,124
A	0.02	.90	<.001	1,144
T_{er}	1.80	.18	0.01	1,144
*v*Go	14.72	<.001	0.09	1,144
*v*NoGo	7.18	.01	0.05	1,144
z/a	1.21	.27	0.008	1,144
Event rate				
RT	28.62	<.001	0.17	1,144
SDRT	0.66	.42	<.001	1,144
Commissions	9.47	<.001	0.06	1,144
Omissions	0.00	.96	<.001	1,144
A'	2.02	.16	0.02	1,124
B''	33.58	<.001	0.21	1,124
A	2.28	.13	0.02	1,144
T_{er}	19.53	<.001	0.12	1,144
*v*Go	0.04	.84	<.001	1,144
*v*NoGo	3.00	.09	0.02	1,144
z/a	2.85	.09	0.01	1,144

Note. SDRT = standard deviation of reaction time; a = boundary separation; Ter = non-decision time; vGo = drift rate to Go decision; vNoGo = drift rate to No Go decision; z/a = relative distance between the start point and no-go boundary; RT = reaction time; ADHD = attention deficit hyperactivity disorder. Signal detection parameters cannot be calculated in the absence of errors, explaining the slightly reduced *df*s used for those comparisons.

Table 4
Table of Statistics for Difficulty Manipulation

	F	*p*	η_p^2	*df*
Within-subject factors				
Block				
RT	25.50	<.001	0.20	
SDRT	0.26	.61	<.001	
Commissions	42.62	<.001	0.29	
Omissions	15.25	<.001	0.13	
A'	0.48	.49	0.01	
B''	33.87	<.001	0.27	
a	<.001	.97	<.001	
T_{er}	0.73	.40	0.01	
*v*Go	<.001	.96	<.001	
*v*NoGo	0.84	.36	0.01	
z/a	11.78	.001	0.10	
Block × ADHD				
RT	2.22	.14	0.02	
SDRT	0.03	.85	<.001	
Commissions	0.27	.60	<.001	
Omissions	3.01	.09	0.03	
A'	0.95	.33	0.01	
B''	2.32	.13	0.02	
a	0.99	.32	0.01	
T_{er}	0.22	.64	<.001	
*v*Go	1.11	.30	0.01	
*v*NoGo	7.98	.01	0.07	
z/a	1.41	.24	0.01	
Block × Difficulty				
RT	3.29	.07	0.03	
SDRT	0.34	.56	<.001	
Commissions	14.55	<.001	0.12	
Omissions	0.02	.88	<.001	
A'	4.07	.05	0.04	
B''	0.23	.63	<.001	
a	1.82	.18	0.02	
T_{er}	0.41	.52	<.001	
*v*Go	<.001	.99	<.001	
*v*NoGo	6.41	.01	0.06	
z/a	1.34	.24	0.01	
Between-subject factors				
ADHD				
RT	4.43	.04	0.04	1,102
SDRT	15.87	<.001	0.13	1,102
Commissions	2.24	.14	0.02	1,102
Omissions	12.70	<.001	0.11	1,102
A'	9.65	<.001	0.09	1,93
B''	0.61	.44	0.01	1,93
a	0.08	.77	<.001	1,102
T_{er}	0.47	.49	<.001	1,102
*v*Go	15.25	<.001	0.13	1,102
*v*NoGo	9.95	<.001	0.09	1,102
z/a	0.74	.39	0.007	1,102
Difficulty				
RT	3.13	.08	0.03	1,102
SDRT	5.26	.02	0.05	1,102
Commissions	49.25	<.001	0.33	1,102
Omissions	12.26	<.001	0.11	1,102
A'	20.35	<.001	0.18	1,93
B''	40.88	<.001	0.31	1,93
a	26.66	<.001	0.21	1,102
T_{er}	0.02	.88	<.001	1,102
*v*Go	5.61	.02	0.05	1,102
*v*NoGo	28.80	<.001	0.22	1,102
z/a	<.001	.99	<.001	1,102

Note. SDRT = standard deviation of reaction time; a = boundary separation; Ter = non-decision time; vGo = drift rate to Go decision; vNoGo = drift rate to No Go decision; z/a = relative distance between the start point and no-go boundary; RT = reaction time; ADHD = attention deficit hyperactivity disorder. Signal detection parameters cannot be calculated in the absence of errors, explaining the slightly reduced *df*s used for those comparisons.

of diagnosis in which children with ADHD performed more poorly overall than non-ADHD controls. The Block × ADHD interaction was not significant for any standard outcome variables (i.e., RT, SDRT, errors; all $p > .09$, $\eta_p^2 < 0.03$).

Model-based task variables. As before, the vigilance decrement was driven by changes in bias in which B'' shifted toward "no, target absent," and the relative start point of the decision process (*z/a*) moved closer to the no-go boundary with time on task, block effect for B'': $F(1, 93) = 33.87$, $p < .001$, $\eta_p^2 = 0.27$ 28, where mean and standard error of Block 1 $B'' = 0.19$ (0.04) and Block 2 $B'' = 0.41$ (0.04); block effect for *z/a:* $F(1, 102) = 11.78$, $p = .001$, $\eta_p^2 = 0.10$, where mean and standard error of Block 1 $z/a = 0.53$ (0.01) and Block 2 $z/a = 0.47$ (0.01). There were no changes in sensitivity with time on task (i.e., block effect for A', *v*Go, and *v*NoGo, all $p > 0.36$, all $\eta_p^2 < 0.01$), but as would be expected, sensitivity was generally lower for the paradigm with more difficult stimuli (difficulty effect for A', *v*Go, and *v*NoGo, all $p < .02$, all $\eta_p^2 > 0.05$). Bias was reduced and boundary separation was smaller for the more difficult paradigm (difficulty effect for B'' and *z*, both $p < .01$, both $\eta_p^2 > 0.07$; difficulty effect for boundary, $p < .001$, $\eta_p^2 = 0.21$). Unlike event rate, manipulating the difficulty of the decisions moderated the vigilance decrement. For the paradigm with more difficult stimuli, there was a relative decrease in the number of commissions with time on task. Although the number of commissions was still higher in the difficult versus easy discriminations at both time points, there was a greater reduction in number of commissions between blocks for difficult versus easy stimuli. This process that was driven by an increase in drift rate to NoGo decisions, Block × Difficulty: commissions: $F(1, 102) = 14.55$, $p < .001$, $\eta_p^2 = 0.12$; *v*NoGo: $F(1, 102) = 6.41$, $p = .02$, $\eta_p^2 = 0.06$.

Poor performance among children with ADHD was driven by reduced sensitivity to distinguish targets from nontargets (diagnosis effect for A', *v*Go, *v*NoGo, all $p < .001$, all $\eta_p^2 > 0.09$), and there were no group differences in bias (diagnosis effect for B'' and *z*, both $p > .43$, both $\eta_p^2 = 0.01$). A significant Block × ADHD interaction for *v* to NoGo, $F(1, 102) = 7.98$, $p = 0.006$, $\eta_p^2 = 0.07$, was also found. Among children with ADHD, *v* to NoGo sped up with time on task, $F(1, 63) = 5.89$, $p = .02$, $\eta_p^2 = 0.09$; mean and standard error Block 1 = −0.29 (0.02), Block 2 = −0.33 (0.02). However, there was no effect of time on task on *v*NoGo for controls, $F(1, 38) = 1.52$, $p = .22$, $\eta_p^2 = 0.04$; mean and standard error Block 1 = −0.37 (0.02), Block 2 = −0.34 (0.02).

Comparison of All Three CPTs

Because data from the basic task was used as the comparison condition in both of the above analyses, we also compared all three tasks together in a single large 2 (Block: first vs. last half) × 3 (Task: easy/slow vs. easy/fast vs. hard/slow) × 2 (Diagnosis: ADHD vs. control) mixed between- and within-subjects ANOVA. The Block × Task × ADHD interaction was not significant for any dependent variable and, thus, was removed from the model. The pattern of results was similar and did not change interpretation with the following exception. A small but significant Block × ADHD interaction was found for *v*Go, $F(1, 183) = 3.89$, $p = 0.05$, $\eta^2 = 0.02$. Follow-up analyses found no main effect of block for either group for *v*Go, though controls demonstrated a modest increase in *v*Go with time on task, $F(1, 58) = 3.45$, $p = .07$, $\eta_p^2 = 0.06$, compared to children with ADHD, $F(1, 127) = 0.41$, $p = 0.52$, $\eta_p^2 = 0.003$.

Discussion

In the current study and across all three tasks, we effectively induced a vigilance decrement in which performance deteriorated over time. For both children with ADHD and non-ADHD controls, this decrement was driven by changes in response bias as indexed by the SDT parameter B'' and the DM parameter *z/a*. These findings are consistent with existing arguments that the vigilance decrement is caused by observers slowly biasing their responses to match the low signal base rate of the CPT (Thomson et al., 2016). In fact, both changes in start point and time-on-task effects are mediated by overlapping frontoparietal brain networks (Langner & Eickhoff, 2013; Mulder et al., 2012). This network of structures includes the midlateral prefrontal cortex, which continuously monitors for external task-relevant events, and the intraparietal sulcus, which is associated with target detection and the perception-driven reorientation of attention.

When laboratory vigilance tasks were first developed in the 1950s, event rates commonly averaged only 5–6 events per hour (to mimic the experiences of radar operators). At such a low event rate, changes in sensitivity over time (e.g., A') were difficult to induce or observe compared to changes in bias. Subsequent research found that changes in sensitivity could be seen if event rates were sufficiently frequent (i.e., >24 events/minute) or if targets differed from nontargets in degree rather than type (Parasuraman, 1979; Parasuraman & Davies, 1977; Thomson et al., 2016). In the current study, we manipulated both event rate and difficulty of discrimination to increase the probability of detecting sensitivity changes if present. Faster event rates did not influence the size of the vigilance decrement, possibly because the differences in conditions were small (i.e., an average of 33 vs. 37 events per minute). However, increasing the difficulty of the discrimination led to a steeper reduction over time in the number of commission errors. This effect was driven by a slight increase in *v* to NoGo (but not *v* to Go) decisions. This means that manipulating difficulty actually lead to a slight improvement in sensitivity over time, rather than a decrement. Boundary separation was smaller and bias to no-go was reduced for more versus less difficult decisions, suggesting that increasing difficulty lead children to be slightly more willing to say "yes, target present," as well as generally be less cautious in their approach to the task.

The ability to sustain one's attention is one of many forms of cognitive or effortful control. Cognitive control is commonly conceptualized as a reactive process, one initiated or invoked *in response to* an external signal such as the detection of conflict, a stop signal, or the commission of an error (Botvinick & Cohen, 2014; Logan, Van Zandt, Verbruggen, & Wagenmakers, 2014). However, proactive forms of control, or control engaged by the internal goals of the individual, and prior to a situation in which reactive control is necessary, is equally necessary for effective behavioral regulation (Aron, 2011). Adjusting the start point of the decision process (*z*) can be seen as a rudimentary form of proactive control that adaptively biases action selection toward the more probable response (Verbruggen, McLaren, & Chambers, 2014). In many situations, bias *toward* action selection facilitates performance because it results in an increase in response readiness.

That being said, maintaining a readiness to respond incurs both computational and opportunity costs. Computational costs are incurred because cognitive processing capacity is not limitless, and opportunity costs are incurred because engagement in one task precludes pursuit of another. From a behavioral economic perspective, the affective experiences of "effort" and "boredom" are the experiential representations of these costs, which encourages disengagement and the subsequent recoupment of those costs (Westbrook & Braver, 2015; Westgate & Wilson, 2018). In the context of a vigilance task when targets are rare, shifting the bias setting reduces the state of preparedness. This, in turn, functionally allows for the search or pursuit of other, potentially more rewarding or meaningful activities with greater benefit (Gable, Hopper, & Schooler, 2019). Indeed, some have argued that the vigilance decrement should not be viewed as a decrement in performance at all but as a positive adaptation to the (low) demands of the task (Hancock, 2013).

We found no evidence of ADHD-related group differences in bias settings (i.e., the main effect of diagnosis and the Block × ADHD interaction for B'' and *z/a* were not significant; both groups were biased to no-go). Interestingly, however, *v*NoGo became faster with time (more negative) for children with ADHD but not controls. This suggests the potential presence of a second mechanism in ADHD that further biases their information processing against a response during a period of vigil. That omissions did not concurrently increase is consistent with interpretations of Hancock (2013) and others that the vigilance decrement may be an adaptive process.

Huang-Pollock et al. (2017) used a 75:25 ratio of targets to nontargets so that the majority of the signals were go and required a bias toward action (i.e., a standard go-no-go type task). Under fast event rates, both groups showed a response bias to go, as would be expected. However, when event rate was slowed (so that most of the time, no response was required, even though most of the signals were go), start point biased to no-go for children with ADHD. Non-ADHD controls maintained a bias to go regardless of event rate. Those findings, combined with findings from the current study, suggest that children with ADHD are particularly responsive to the cost of allocating cognitive resources toward a task. These biases are subtle, however, and would not have been observed if analyses were restricted to standard indices of performance, highlighting the utility of the diffusion model.

Yet the cost of task engagement is not absolute; it depends upon the availability and the valuation of alternatives. For example, manipulations that increase the reward value or reward rate of targets, the meaningfulness of the work, and even more simply, the ratio of targets to nontargets, have all been found to improve engagement or reduce the vigilance decrement (Evans et al., 2013; Methot & Huitema, 1998; Shiels et al., 2008; Westgate & Wilson, 2018). Altered motivation and reward responsiveness have long featured in etiologic theories of ADHD (Volkow et al., 2009), suggesting that nonnormative evaluation of the task or task alternatives may contribute to ADHD-related sensitivity to the cost of engagement. However, empirical evidence remains somewhat inconsistent (Luman, Oosterlaan, & Sergeant, 2005). More recent work in effort discounting (Chevalier, 2018; Lopez-Gamundi & Wardle, 2018) may provide a novel method by which individual differences in the valuation of cognitive effort can be directly and efficiently measured.

Costs can also be reduced through practice and the development of task-specific automaticity (Logan, 2018), including for tasks of sustained attention (Parasuraman & Giambra, 1991). Tasks that at one time required focused attention no longer require that control following practice. There is evidence that even after extensive practice, children with ADHD are never able to acquire the same level of skill as their nonaffected and IQ-matched counterparts (Huang-Pollock & Karalunas, 2010; Weigard, Huang-Pollock, & Brown, 2016). Thus, the apparent bias to task disengagement in ADHD may be due to the fact that computational costs do not decrease to the same extent with practice.

Does this sensitivity to costs/benefits of allocating resources toward a task indicate the presence of a sustained attention deficit among children with ADHD? Vigilance has traditionally been defined as the capacity to maintain a readiness to respond to rare targets, and the vigilance decrement was operationalized as error rate over time. This specific operationalization was chosen based on its relevance to the real-world behavior of interest at the time that the study of vigilance was born: experiences of radar operators in the detection of enemy aircraft. With this definition and operationalization, we found no evidence of a *sustained attention* deficit among children with ADHD. Consistent with findings from a previous meta-analytic review that found performance-over-time effects to be quite small (Huang-Pollock et al., 2012), performance did not decrease to a greater degree over time among children with ADHD, even when the task was made more difficult through difficulty or event rate manipulations.

Alternative definitions of sustained attention do exist, some of which include short-term phasic arousal, as measured by greater standard deviation of RT, and do not require a deficit over longer periods of time (e.g., Bellgrove, Hawi, Gill, & Robertson, 2006; Robertson, Manly, Andrade, Baddeley, & Yiend, 1997). However, the core of the construct of sustained attention is the maintenance of a bias or a willingness to engage in a task (Sarter, Gehring, & Kozak, 2006). Bias measures (indexed by changes in *z/a* or faster *v*NoGo) may, therefore, better operationalize failures of sustained attention, with the added benefit that such indices take into account both the accuracy and speed of response. This reevaluation and reoperationalization of the construct of sustained attention improves its alignment with current theories of cognitive control, as well as the mechanisms and processes that support that control. Defined in this way, we found modest evidence of a vigilance deficit in ADHD. The effect size for the ADHD × Block interaction for *v* to NoGo, which was the only dependent variable to reach significance, was small.

The larger effect was that children with ADHD underperformed their same-aged peers at all time points due to reduced sensitivity to discriminate targets from nontargets (A' and *v* to both Go and NoGo decisions were smaller/slower). This finding of reduced sensitivity is consistent with previous meta-analytic reviews of the CPT literature in ADHD (Huang-Pollock et al., 2012; Losier et al., 1996), as well as a growing body of literature that has documented slow drift rates in children with ADHD more generally (Huang-Pollock et al., 2017; Karalunas & Huang-Pollock, 2013; Karalunas, Huang-Pollock, & Nigg, 2012; Weigard & Huang-Pollock, 2017; Weigard, Huang-Pollock, Brown, & Heathcote, 2018). Thus, the better conceptualization of ADHD-related cognitive atypicality is likely not a reduced capacity to maintain a bias to engage but, rather, slower accumulation of evidence to make a decision, as indexed by drift rate.

We note that drift rate is influenced by both accuracy of response and intraindividual variability of RT—notably, those RTs located in the tail of the distribution (Ratcliff, Smith, Brown, & McKoon, 2016). Those RTs have also been found to be predictive of higher-order cognitive processes including intellectual ability and executive functions (Balota & Yap, 2011; Karalunas & Huang-Pollock, 2013; Ratcliff, Schmiedek, & McKoon, 2008). Although intraindividual variability has most commonly been represented by the standard deviation of RT, use of the better-specified DM parameters represents a significant advancement in the isolation and interpretation of individual differences in cognition.

The existing body of work in sustained attention in ADHD rarely reports performance-over-time data. It also tends to adopt simple paradigms that produce high accuracy/low error rates, which in turn reduces the interpretability of the SDT parameters. Thus, clear strengths of the study were the reporting of time-on-task data, use of target and nontarget stimuli that were not easily distinguishable, and leveraging RT distributions using the DM that allow these measures to be understood in the context of a unified model. These improvements in paradigm construction produced the moderate error rates necessary for the accurate interpretation of SDT parameters. In fact, with the exception of identifying a small ADHD × Block effect for *v*NoGo, results from our SDT and DM analyses were largely similar. Even in this case, however, 10–11% of participants of both diagnostic groups performed perfectly and had to be dropped from SDT analyses. Thus, we recommend future studies continue to use targets that are not easily distinguishable from nontargets and to make full use of the data available by reporting and interpreting DM parameters (for recommendations on how to handle low-error tasks, see Ratcliff, 2014). It may also be useful to continue evaluating the boundary conditions upon which ADHD-related bias toward disengagement can best be observed and measured. Although it is clear that children with ADHD have day-to-day difficulties sustaining attention to complete homework and chores, such activities do not easily lend themselves to neurocognitive investigation because of the multidimensional nature of those tasks. Thus, it would be important for future studies to develop paradigms that are amenable to neurocognitive investigation while also tapping the core behaviors of interests.

A clear limitation of the study was in the use of a between- as opposed to within-subjects design to evaluate the influence of event rate and difficulty manipulations on performance, as well as unequal sample sizes. Unequal sample sizes also likely contributed to low power to detect three-way interactions if they existed (and which were removed from our GLMs). Power is, of course, a function of both sample and effect size. Given the small effect sizes found in the current study, future studies would need to plan to recruit a substantially larger sample size to obtain a significant three-way interaction.

We further note that the number of CPT variants developed for studies in cognitive psychology are as diverse as the questions that prompt their individual development. However, all are defined by the presence of “rare” targets; those used in the study of ADHD have ranged between 3% and 30% (e.g., Tsal, Shalev, & Mevorach, 2005; Tucha et al., 2009), though 10% is commonly chosen. For the purposes of the current study, we chose a target rate of 25% to balance the definitional requirement of “rare” against the need to collect enough responses within a reasonable amount of time to allow the DM parameters to be modeled. Because they provide at most half the number of trial data/responses and index similar core information processes, recent work has suggested that two-choice tasks may be preferred over one-choice tasks like the go-no-go and CPT (Gomez, Ratcliff, & Perea, 2007; Ratcliff et al., 2018). Future studies might consider adopting a two-choice paradigm.

Summary and Conclusions

The ability to sustain attention is critical to the success of a range of daily activities, and difficulty maintaining attention is a central behavioral feature of ADHD. However, for multiple experimental design and data reporting reasons, the status of sustained attention in ADHD remains unresolved. In the current study, we found that children with ADHD demonstrated a modest processing bias against a response during a period of vigil. Although bias measures as indexed by the DM parameters *z/a* or *v*NoGo may better reflect current conceptualization of vigilance, and argue for a sustained attention deficit in ADHD, the larger effect was not in an inability to maintain engagement but in slow drift rate throughout the duration of the tasks.

References

Aron, A. R. (2011). From reactive to proactive and selective control: Developing a richer model for stopping inappropriate responses. *Biological Psychiatry, 69*(12), e55–e68. http://dx.doi.org/10.1016/j.biopsych.2010.07.024

Balota, D. A., & Yap, M. J. (2011). Moving beyond the mean in studies of mental chronometry: The power of response time distributional analyses. *Current Directions in Psychological Science, 20,* 160–166. http://dx.doi.org/10.1177/0963721411408885

Bellgrove, M. A., Hawi, Z., Gill, M., & Robertson, I. H. (2006). The cognitive genetics of attention deficit hyperactivity disorder (ADHD): Sustained attention as a candidate phenotype. *Cortex: A Journal Devoted to the Study of the Nervous System and Behavior, 42,* 838–845. http://dx.doi.org/10.1016/S0010-9452(08)70426-X

Berkson, J. (1946). Limitations of the application of fourfold table analysis to hospital data. *Biometrics Bulletin, 2,* 47–53. http://dx.doi.org/10.2307/3002000

Blanca, M. J., Alarcón, R., Arnau, J., Bono, R., & Bendayan, R. (2017). Non-normal data: Is ANOVA still a valid option? *Psicothema, 29,* 552–557. http://dx.doi.org/10.7334/psicothema2016.383

Botvinick, M. M., & Cohen, J. D. (2014). The computational and neural basis of cognitive control: Charted territory and new frontiers. *Cognitive Science, 38,* 1249–1285. http://dx.doi.org/10.1111/cogs.12126

Chevalier, N. (2018). Willing to think hard? The subjective value of cognitive effort in children. *Child Development, 89,* 1283–1295. http://dx.doi.org/10.1111/cdev.12805

Cohen, P., & Cohen, J. (1984). The clinician’s illusion. *Archives of General Psychiatry, 41,* 1178–1182. http://dx.doi.org/10.1001/archpsyc.1984.01790230064010

Conners, K. (1997). *Conners’ Rating Scales-Revised technical manual*. New York, NY: Multi Health Systems.

DuPaul, G., Power, T., Anastopoulos, A., & Reid, R. (1998). *ADHD Rating Scale-IV: Checklists, norms, and clinical interpretation*. New York, NY: Guilford Press.

Evans, K. K., Birdwell, R. L., & Wolfe, J. M. (2013). If you don’t find it often, you often don’t find it: Why some cancers are missed in breast cancer screening. *PLoS ONE, 8*(5), e64366. http://dx.doi.org/10.1371/journal.pone.0064366

Gable, S. L., Hopper, E. A., & Schooler, J. W. (2019). When the muses strike: Creative ideas of physicists and writers routinely occur during mind wandering. *Psychological Science, 30,* 396–404. http://dx.doi.org/10.1177/0956797618820626

Gomez, P., Ratcliff, R., & Perea, M. (2007). A model of the go/no-go task. *Journal of Experimental Psychology: General, 136,* 389–413. http://dx.doi.org/10.1037/0096-3445.136.3.389

Goodman, S. H., Lahey, B. B., Fielding, B., Dulcan, M., Narrow, W., & Regier, D. (1997). Representativeness of clinical samples of youths with mental disorders: A preliminary population-based study. *Journal of Abnormal Psychology, 106,* 3–14. http://dx.doi.org/10.1037/0021-843X.106.1.3

Grobbee, D., & Hoes, A. (2015). *Clinical epidemiology: Principles, methods, and applications for clinical research*. Burlington, MA: Jones and Bartlett Learning, LLC.

Hancock, P. A. (2013). In search of vigilance: The problem of iatrogenically created psychological phenomena. *American Psychologist, 68,* 97–109. http://dx.doi.org/10.1037/a0030214

Huang-Pollock, C. L., & Karalunas, S. L. (2010). Working memory demands impair skill acquisition in children with ADHD. *Journal of Abnormal Psychology, 119,* 174–185. http://dx.doi.org/10.1037/a0017862

Huang-Pollock, C. L., Karalunas, S. L., Tam, H., & Moore, A. N. (2012). Evaluating vigilance deficits in ADHD: A meta-analysis of CPT performance. *Journal of Abnormal Psychology, 121,* 360–371. http://dx.doi.org/10.1037/a0027205

Huang-Pollock, C., Ratcliff, R., McKoon, G., Shapiro, Z., Weigard, A., & Galloway-Long, H. (2017). Using the diffusion model to explain cognitive deficits in attention deficit hyperactivity disorder. *Journal of Abnormal Child Psychology, 45,* 57–68. http://dx.doi.org/10.1007/s10802-016-0151-y

Karalunas, S. L., & Huang-Pollock, C. L. (2013). Integrating impairments in reaction time and executive function using a diffusion model framework. *Journal of Abnormal Child Psychology, 41,* 837–850. http://dx.doi.org/10.1007/s10802-013-9715-2

Karalunas, S. L., Huang-Pollock, C. L., & Nigg, J. T. (2012). Decomposing attention-deficit/hyperactivity disorder (ADHD)-related effects in response speed and variability. *Neuropsychology, 26,* 684–694. http://dx.doi.org/10.1037/a0029936

Koelega, H. S., Brinkman, J.-A., Hendriks, L., & Verbaten, M. N. (1989). Processing demands, effort, and individual differences in four different vigilance tasks. *Human Factors, 31,* 45–62. http://dx.doi.org/10.1177/001872088903100104

Lahey, B. B., Applegate, B., McBurnett, K., Biederman, J., Greenhill, L., Hynd, G. W., . . . Shaffer, D. (1994). *DSM–IV* field trials for attention deficit hyperactivity disorder in children and adolescents. *The American Journal of Psychiatry, 151,* 1673–1685. http://dx.doi.org/10.1176/ajp.151.11.1673

Langner, R., & Eickhoff, S. B. (2013). Sustaining attention to simple tasks: A meta-analytic review of the neural mechanisms of vigilant attention. *Psychological Bulletin, 139,* 870–900. http://dx.doi.org/10.1037/a0030694

Leite, F. P., & Ratcliff, R. (2011). What cognitive processes drive response biases? A diffusion model analysis. *Judgment and Decision Making, 6,* 651–687. Retrieved from https://psycnet.apa.org/record/2011-24967-007

Logan, G. D. (2018). Automatic control: How experts act without thinking. *Psychological Review, 125,* 453–485. http://dx.doi.org/10.1037/rev0000100

Logan, G. D., Van Zandt, T., Verbruggen, F., & Wagenmakers, E.-J. (2014). On the ability to inhibit thought and action: General and special theories of an act of control. *Psychological Review, 121,* 66–95. http://dx.doi.org/10.1037/a0035230

Lopez-Gamundi, P., & Wardle, M. C. (2018). The cognitive effort expenditure for rewards task (C-EEfRT): A novel measure of willingness to expend cognitive effort. *Psychological Assessment, 30,* 1237–1248. http://dx.doi.org/10.1037/pas0000563

Losier, B. J., McGrath, P. J., & Klein, R. M. (1996). Error patterns on the continuous performance test in non-medicated and medicated samples of children with and without ADHD: A meta-analytic review. *Journal of Child Psychology and Psychiatry, 37,* 971–987. http://dx.doi.org/10.1111/j.1469-7610.1996.tb01494.x

Luman, M., Oosterlaan, J., & Sergeant, J. A. (2005). The impact of reinforcement contingencies on AD/HD: A review and theoretical appraisal. *Clinical Psychology Review, 25,* 183–213. http://dx.doi.org/10.1016/j.cpr.2004.11.001

Mackworth, N. H. (1948). The breakdown of vigilance during prolonged visual search. *The Quarterly Journal of Experimental Psychology, 1,* 6–21. http://dx.doi.org/10.1080/17470214808416738

Methot, L. L., & Huitema, B. E. (1998). Effects of signal probability on individual differences in vigilance. *Human Factors, 40,* 102–110. http://dx.doi.org/10.1518/001872098779480514

Meuter, R. F. I., & Lacherez, P. F. (2016). When and why threats go undetected: Impacts of event rate and shift length on threat detection accuracy during airport baggage screening. *Human Factors, 58,* 218–228. http://dx.doi.org/10.1177/0018720815616306

Mulder, M. J., Wagenmakers, E. J., Ratcliff, R., Boekel, W., & Forstmann, B. U. (2012). Bias in the brain: A diffusion model analysis of prior probability and potential payoff. *The Journal of Neuroscience, 32,* 2335–2343. http://dx.doi.org/10.1523/JNEUROSCI.4156-11.2012

Parasuraman, R. (1979). Memory load and event rate control sensitivity decrements in sustained attention. *Science, 205,* 924–927. http://dx.doi.org/10.1126/science.472714

Parasuraman, R., & Davies, D. (1977). A taxonomic analysis of vigilance performance. In R. Mackie (Ed.), *Vigilance* (Vol. 3, pp. 559–574). Boston, MA: Springer. http://dx.doi.org/10.1007/978-1-4684-2529-1_26

Parasuraman, R., & Giambra, L. (1991). Skill development in vigilance: Effects of event rate and age. *Psychology and Aging, 6,* 155–169. http://dx.doi.org/10.1037/0882-7974.6.2.155

Ratcliff, R. (1978). Theory of memory retrieval. *Psychological Review, 85,* 59–108. http://dx.doi.org/10.1037/0033-295X.85.2.59

Ratcliff, R. (1985). Theoretical interpretations of the speed and accuracy of positive and negative responses. *Psychological Review, 92,* 212–225. http://dx.doi.org/10.1037/0033-295X.92.2.212

Ratcliff, R. (2014). Measuring psychometric functions with the diffusion model. *Journal of Experimental Psychology: Human Perception and Performance, 40,* 870–888. http://dx.doi.org/10.1037/a0034954

Ratcliff, R., Huang-Pollock, C., & McKoon, G. (2018). Modeling individual differences in the go/no-go task with a diffusion model. *Decision, 5,* 42–62. http://dx.doi.org/10.1037/dec0000065

Ratcliff, R., Love, J., Thompson, C. A., & Opfer, J. E. (2012). Children are not like older adults: A diffusion model analysis of developmental changes in speeded responses. *Child Development, 83,* 367–381. http://dx.doi.org/10.1111/j.1467-8624.2011.01683.x

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation, 20,* 873–922. http://dx.doi.org/10.1162/neco.2008.12-06-420

Ratcliff, R., Schmiedek, F., & McKoon, G. (2008). A diffusion model explanation of the worst performance rule for reaction time and IQ. *Intelligence, 36,* 10–17. http://dx.doi.org/10.1016/j.intell.2006.12.002

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion decision model: Current issues and history. *Trends in Cognitive Sciences, 20,* 260–281. http://dx.doi.org/10.1016/j.tics.2016.01.007

Ratcliff, R., Thapar, A., & McKoon, G. (2010). Individual differences, aging, and IQ in two-choice tasks. *Cognitive Psychology, 60,* 127–157. http://dx.doi.org/10.1016/j.cogpsych.2009.09.001

Ratcliff, R., Thapar, A., & McKoon, G. (2011). Effects of aging and IQ on item and associative memory. *Journal of Experimental Psychology: General, 140,* 464–487. http://dx.doi.org/10.1037/a0023810

Ratcliff, R., & Tuerlinckx, F. (2002). Estimating parameters of the diffusion model: Approaches to dealing with contaminant reaction times and parameter variability. *Psychonomic Bulletin & Review, 9,* 438–481. http://dx.doi.org/10.3758/BF03196302

Reynolds, C., & Kamphaus, R. (1992). *Behavior Assessment System for Children: Manual*. Circle Pines, MN: American Guidance Service, Inc.

Riccio, C. A., Reynolds, C. R., Lowe, P., & Moore, J. J. (2002). The continuous performance test: A window on the neural substrates for attention? *Archives of Clinical Neuropsychology, 17,* 235–272. http://dx.doi.org/10.1093/arclin/17.3.235

Robertson, I. H., Manly, T., Andrade, J., Baddeley, B. T., & Yiend, J. (1997). 'Oops!': Performance correlates of everyday attentional failures in traumatic brain injured and normal subjects. *Neuropsychologia, 35,* 747–758. http://dx.doi.org/10.1016/S0028-3932(97)00015-8

Sarter, M., Gehring, W. J., & Kozak, R. (2006). More attention must be paid: The neurobiology of attentional effort. *Brain Research Reviews, 51,* 145–160. http://dx.doi.org/10.1016/j.brainresrev.2005.11.002

Sarter, M., Givens, B., & Bruno, J. P. (2001). The cognitive neuroscience of sustained attention: Where top-down meets bottom-up. *Brain Research Reviews, 35,* 146–160. http://dx.doi.org/10.1016/S0165-0173(01)00044-3

See, J. E., Warm, J. S., Dember, W. N., & Howe, S. R. (1997). Vigilance and signal detection theory: An empirical evaluation of five measures of response bias. *Human Factors, 39,* 14–29. http://dx.doi.org/10.1518/001872097778940704

Shaffer, D., Fisher, P., & Lucas, R. (1997). *NIMH Diagnostic Interview Schedule for Children-IV*. New York, NY: Ruane Center for Early Diagnosis, Division of Child Psychiatry, Columbia University.

Shiels, K., Hawk, L. W., Jr., Lysczek, C. L., Tannock, R., Pelham, W. E., Jr., Spencer, S. V., . . . Waschbusch, D. A. (2008). The effects of incentives on visual-spatial working memory in children with attention-deficit/hyperactivity disorder. *Journal of Abnormal Child Psychology, 36,* 903–913. http://dx.doi.org/10.1007/s10802-008-9221-0

Stanislaw, H., & Todorov, N. (1999). Calculation of signal detection theory measures. *Behavior Research Methods, Instruments & Computers, 31,* 137–149. http://dx.doi.org/10.3758/BF03207704

Thomson, D. R., Besner, D., & Smilek, D. (2016). A critical examination of the evidence for sensitivity loss in modern vigilance tasks. *Psychological Review, 123,* 70–83. http://dx.doi.org/10.1037/rev0000021

Tsal, Y., Shalev, L., & Mevorach, C. (2005). The diversity of attention deficits in ADHD: The prevalence of four cognitive factors in ADHD versus controls. *Journal of Learning Disabilities, 38,* 142–157. http://dx.doi.org/10.1177/00222194050380020401

Tucha, L., Tucha, O., Walitza, S., Sontag, T. A., Laufkötter, R., Linder, M., & Lange, K. W. (2009). Vigilance and sustained attention in children and adults with ADHD. *Journal of Attention Disorders, 12,* 410–421. http://dx.doi.org/10.1177/1087054708315065

Verbruggen, F., McLaren, I. P. L., & Chambers, C. D. (2014). Banishing the control homunculi in studies of action control and behavior change. *Perspectives on Psychological Science, 9,* 497–524. http://dx.doi.org/10.1177/1745691614526414

Volkow, N. D., Wang, G. J., Kollins, S. H., Wigal, T. L., Newcorn, J. H., Telang, F., . . . Swanson, J. M. (2009). Evaluating dopamine reward pathway in ADHD: Clinical implications. *Journal of the American Medical Association, 302,* 1084–1091. http://dx.doi.org/10.1001/jama.2009.1308

Voss, A., Nagler, M., & Lerche, V. (2013). Diffusion models in experimental psychology: A practical introduction. *Experimental Psychology, 60,* 385–402. http://dx.doi.org/10.1027/1618-3169/a000218

Wagenmakers, E.-J., van der Maas, H. L. J., & Grasman, R. P. P. P. (2007). An EZ-diffusion model for response time and accuracy. *Psychonomic Bulletin & Review, 14,* 3–22. http://dx.doi.org/10.3758/BF03194023

Wechsler, D. (2003). *Wechsler Intelligence Scale for Children, 4th ed. (WISC-IV): Technical and interpretive manual*. San Antonio, TX: Harcourt Brace.

Weigard, A., & Huang-Pollock, C. (2017). The role of speed in ADHD-related working memory deficits: A time-based resource-sharing and diffusion model account. *Clinical Psychological Science, 5,* 195–211. http://dx.doi.org/10.1177/2167702616668320

Weigard, A., Huang-Pollock, C., & Brown, S. (2016). Evaluating the consequences of impaired monitoring of learned behavior in attention-deficit/hyperactivity disorder using a Bayesian hierarchical model of choice response time. *Neuropsychology, 30,* 502–515. http://dx.doi.org/10.1037/neu0000257

Weigard, A., Huang-Pollock, C., Brown, S., & Heathcote, A. (2018). Testing formal predictions of neuroscientific theories of ADHD with a cognitive model-based approach. *Journal of Abnormal Psychology, 127,* 529–539. http://dx.doi.org/10.1037/abn0000357

Westbrook, A., & Braver, T. S. (2015). Cognitive effort: A neuroeconomic approach. *Cognitive, Affective & Behavioral Neuroscience, 15,* 395–415. http://dx.doi.org/10.3758/s13415-015-0334-y

Westgate, E. C., & Wilson, T. D. (2018). Boring thoughts and bored minds: The MAC model of boredom and cognitive engagement. *Psychological Review, 125*(5), 689–713. http://dx.doi.org/10.1037/rev0000097

White, C. N., & Poldrack, R. A. (2014). Decomposing bias in different types of simple decisions. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 40,* 385–398. http://dx.doi.org/10.1037/a0034851

Witt, J. K., Taylor, J. E. T., Sugovic, M., & Wixted, J. T. (2015). Signal detection measures cannot distinguish perceptual biases from response biases. *Perception, 44,* 289–300. http://dx.doi.org/10.1068/p7908

Received October 10, 2019
Revision received March 13, 2020
Accepted March 16, 2020 ■