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PREFERENTIAL CHOICE TO EXERT COGNITIVE EFFORT IN CHILDREN WITH ADHD: A DIFFUSION MODELLING ACCOUNT

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Abstract

Background: Motivation deficits have long been implicated in the development and maintenance of ADHD, but study designs based on reward-based improvement remains inconclusive due to potential ceiling effects and limits in the range of reward tested. Preferential choice to engage in demanding tasks may be a better measure of motivation. **Methods:** Children aged 8-12 with (n = 49) and without (n = 36) ADHD were administered the cognitive effort discounting paradigm (COG-ED, adapted from Westbrook et al., 2013) to determine the value children place on effort. Diffusion modelling decomposition of performance provided additional insight into the choice process. **Results**: As expected, all children showed evidence of effort discounting, and discounting choices did not differ by ADHD status. However, children with greater accuracy on the effortful N-back task had steeper discounting curves than children with lower accuracy due to a better mental representation of demand. This was evidenced by greater decision difficulty (v) and response caution (a) to decisions that included higher task loads. Those with ADHD were overrepresented in the group with lower N-back accuracy; they also showed a smaller increase in decision difficulty (v) to decisions that included higher task loads, indicating a less differentiated representation of demand. **Conclusions**: All children demonstrated some capacity for monitoring of task demand, but better performance on the effortful task predicted more accurate metacognitive monitoring. Children with ADHD may have a subtle deficit in demand evaluation, which can impede their adaptive engagement of cognitive effort/control.

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Introduction

Attention-Deficit/Hyperactivity Disorder (ADHD) is a common neurodevelopmental disorder that affects one in 20 children worldwide (Polanczyk et al., 2007). It is characterized by developmentally inappropriate inattention and/or hyperactivity and impulsivity, and is associated with poor outcomes across academic and social emotional domains (Hinshaw, 2002). ADHD has been traditionally conceptualized as a disorder of executive functioning (Barkley, 1997), although significant situational variability in performance has also been observed (Castellanos et al., 2006; Sonuga-Barke et al., 2010). Children with ADHD disengage more quickly from long and challenging tasks (Scime, & Norvilitis, 2006), and "avoids, dislikes, or is reluctant to engage in tasks that require sustained mental effort" is a core symptom of the disorder (DSM-5, American Psychiatric Association, 2013). That behavior has often been conceptualized within an executive function framework as day-to-day evidence of a deficit in sustained attention, although such deficits as cognitively defined have not been substantiated (Huang-Pollock et al., 2012; Huang-Pollock et al., 2020). More recent theorizing have thus begun to consider behavioral economic principles of choice and utility to better explain these behaviors.

Avoiding mental effort is of course ubiquitous to the human condition because it is adaptive (Kool et al., 2010). Whether to allocate cognitive effort is determined by a process that weighs the potential payoff against the costs (Shenhav et al., 2021), including the opportunity cost incurred when a capacity-limited resource, like attention, is deployed in pursuit of a current goal (Kurzban et al., 2013; Shenhav et al., 2017). The implication is that behavioral difficulties associated with ADHD may be due to a shift in this cost-benefit analysis in which children experience a reduced sensitivity to the rewarding property of the payoff and/or an increase in sensitivity towards effort-related costs (Haenlein, & Caul, 1987; Sergeant, 2005). However, evidence of differential reward sensitivities is mixed, and studies finding that larger performance improvements or even performance normalization under reward in ADHD may be confounded by ceiling effects in the control group in which performance cannot appreciably improve further on a given task (Luman et al., 2005). There are also constraints in manipulating reward frequency and intensity, where null results can simply be due to limits in the range of reward tested rather than true absence of group difference in reward functioning (e.g. Slusarek et al., 2001).

The cognitive effort discounting (COG-ED) paradigm was designed to address some of these concerns. Rather than inducing changes in performance via rewards, COG-ED measures the value of effort by the extent to which increasing effort reduces *preference* for reward, (Westbrook et al., 2013). Participants make binary choices between performing a difficult task for larger reward versus an easy task for smaller reward. The subjective value of the difficult task is estimated through a series of choices in which the reward for completion of an easy task is stepwise adjusted so that participants eventually reach an indifference point by the end of the choice period. The COG-ED paradigm thus provides an explicit measure of the value an individual places on effort. Indeed, preferences expressed on the COG-ED predict the probability of participants engaging in mentally or physically demanding activities in their daily life (Culbreth et al., 2020).

Previous studies of preadolescent/adolescent/adult ADHD of *physical* effort discounting have not identified ADHD-related group differences (Mies et al., 2018a; Winter et al., 2019; Addicott et al., 2019) and neither has the single cognitive effort discounting study conducted to date in a small sample of clinic-recruited adolescent boys (15 ADHD and 16 controls) (Mies et al., 2018b).

These early studies suggest that ADHD may not be associated with alteration in effort discounting, at least in adolescence, but a significant drawback of each is that traditional methods of evaluating choice in the COG-ED paradigm only evaluates the final choice made, and does not take into account the process by which these decisions are reached. Both choice and speed are critical to understanding preferential decision making (Bakkour et al., 2019). For example, decision-making biases lead to faster responses for the biased option (Ratcliff, & McKoon, 2008), and more difficult decisions tend to be slower (Bakkour et al., 2019). Thus, where the ultimate decision to engage or not engage in effort for a given reward may be the same between any two individuals or groups, the difficulty of that decision, or the bias towards or away from that decision, is not captured with standard methods that are only concerned with choice.

Sequential sampling models such as the diffusion model assume that speeded decisions are made by gradually accumulating evidence in a stochastic process until a decision threshold is reached and one option is deemed sufficiently better than the other (Ratcliff, & McKoon, 2008). Such models are able to capture both the behavioral (Mormann et al., 2010; Krajbich et al., 2010) and neural (Basten et al., 2010) process of value-based decision making. One parameter of interest is the rate of evidence accumulation (i.e., drift rate), which a function of the individual (e.g. Karalunas et al., 2012) and of the task/stimulus (Ratcliff, & McKoon, 2008). In the context of value-based decisions, evidence is generated internally and reflects moment-to-moment changes in the perceived value of both options (Westbrook et al., 2020). In these situations, drift rate is faster when the value difference between options widens, and is slower when the difference between options is smaller (Frank et al., 2015). For example, someone may decide quickly that completing a 2-back (in a standard N-back working memory task) for $2 is a better option than 1-back for $1 because the 2-back is not that much more difficult, and the reward is greater. Whether to complete a 4-back for $2 vs. 1-back for $1 is generally a more difficult decision to make because the reward is discounted by the increased task load, and the two options are therefore closer in subjective value.

A second parameter of interest is the starting point of evidence accumulation which can be used to identify inherent biases, if any, towards either of the response options. When the start point is biased towards one boundary, it decreases the time needed to choose that option and increases the likelihood that the option is chosen. Diffusion modelling of the effort discounting choices thus has the advantage of accounting for both the choice and the speed of that choice and is able to shed light on the reasons that a decision is made, which goes well beyond the binary choice itself. As an example, a previous study utilizing diffusion modelling in preferential choice found that both response bias and slowed drift rate to the optimal choice explained impaired decision making in addiction (Scherbaum et al., 2018).

The current study evaluated effort discounting among community-recruited school-aged children with and without ADHD. We hypothesized greater task load would be associated with (a) reduced subjective value (i.e. effort discounting) and (b) slower drift rate, as the two options converge in subjective value. We also hypothesized that children with ADHD would show evidence of greater effort discounting. This would be evidenced by (a) smaller subjective value and (b) response bias towards the easy task, across all levels of task load. The diagnostic group difference could also manifest as a group x task load interaction. In this situation, as load increased, children with ADHD would demonstrate (c) larger reduction in subjective value (i.e. steeper discounting) and/or (d) increased slowdown of drift rate.

Methods

Participants

Eighty-five children between 8 and 12 years old with (n = 49) and without (n= 36) ADHD participated. They were recruited through advertisement via local schools, newspaper and radio ads, and fliers distributed throughout Centre County in Pennsylvania. Children who participated were ethnically representative of the region: 86% Caucasian, 5% Caucasian/white Hispanic, 1% other Hispanic, 8% mixed/unknown. Children were excluded from the study if they met one or more of the following: 1) current non-stimulant psychoactive medication treatment; 2) an estimated Full Scale IQ below 80 based on a two-subtest short form (Vocabulary, Matrix Reasoning) of the Wechsler Intelligence Scale for Children-IV (WISC-IV: Wechsler, 2003) or four-subtest short form of the WISC-V (Matrices, Picture Concepts, Digit Span, Picture Span) – both of which have a concurrent validity of 0.87 to the Full Scale IQ (Sattler, 2008; Sattler, 2018); 3) a history of parent-reported psychosis, neurological, developmental, intellectual, or sensorimotor disabilities that would preclude full participation. The data collection was carried out in accordance with the human research ethics of Pennsylvania State University Institutional Review Board (IRB#32126).

Children with ADHD

Children with ADHD met full DSM-5 criteria (any presentation type), including duration, age of onset, and multi-context impairment (American Psychiatric Association, 2013). Parent report of symptomology was obtained via the Diagnostic Interview Schedule for Children-IV (DISC-IV; Shaffer et al., 1997). To demonstrate cross-situational impairment, at least one parent and one teacher report of behavior on the Attention, Hyperactivity, or ADHD subscales of the

Behavioral Assessment Scale or Children (BASC-2/3; Reynolds & Kamphaus, 2004; Reynolds & Kamphaus, 2015) or the Conners' Rating Scales (Conners 3; Conners, 2008) were required to exceed the 85th percentile (i.e., T-score ≥ 61), and at least 3 symptoms were required to be present at an impairing level by teacher report. Following DSM field trials, diagnostic determination and final symptom counts followed an "or" algorithm to integrate parent responses on the DISC with teacher reports on the ADHD Rating Scale (Lahey et al., 1994; DuPaul et al., 1998). Children prescribed stimulant medication ($n = 10$) were asked to discontinue medication use for 24–48 h.

Non-ADHD Controls

Non-ADHD controls did not meet ADHD criteria on DISC-IV, 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 ≤3 total symptoms and ≤2 symptoms per ADHD dimension according to the "or" algorithm. The presence of anxiety, depression, oppositional defiant, and conduct disorders was 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. Compared to controls, children with ADHD had more symptoms of inattention ($F(1, 83) = 829.38$, $p < 0.001$, PRE = 0.91) and hyperactivity/impulsivity ($F(1, 83) = 158.80$, $p < 0.001$, PRE = 0.66). There were no group differences in estimated IQ ($F(1, 83) = 0.04$, $p = 0.85$, PRE = 0.00) or age ($F(1, 83) = 1.38$, $p = 0.24$, PRE = 0.02).

Cognitive Effort Discounting (COG-ED)

The COG-ED task consists of two phases and was directly adapted from Westbrook et al. (2019). During the first phase, participants completed an N-back working memory task to gain familiarity with the subjective demand of each of four levels of task load (1-, 2-, 3- and 4- back). They were given 1.5s to respond to each letter via button press, after which the letter was replaced by a fixation underscore ("_") lasting 3.5s. Participants completed three runs of 33 trials at each task level. All participants completed the task levels in the same order (2-, 1-, 3-, 4-back); they were informed of the task level at the start of each level, and the font color was also uniquely associated with each level.

For the second phase, effort discounting was assessed by binary choices between performing a difficult level of N-back (2-, 3- or 4-back) for larger reward ($2 or $5) versus 1-back for smaller reward. The smaller reward was adjusted following a stepwise procedure. It started as half of the high offer ($1 or $2.5) and was adjusted based on the previous choice, thus approaching an indifference point where the subjective value of the difficult N-back can be estimated. Participants made a total of 36 choices. To ensure the validity of choices, participants were told that one of their choices would be randomly selected at the end and they would be able to earn the reward amount of that choice.

Data Analytic Approach

Five participants were excluded from the final analyses due to missing more than 50% of all the N-back trials, and two more participants were removed due to missing all trials in an entire N-back level. This resulted in a final sample of 46 children with and 32 without ADHD. Descriptive statistics of groups are provided in Table 1.

N-back Performance

Individual N-back trials with RT faster than 300ms were removed prior to analyses (Ratcliff, & Tuerlinckx, 2002), which represented 6% of the total trials. d prime (*d'*) was used as the primary measure of N-back performance (Haatveit et al., 2010). Mixed-effects linear regressions with subject-level random intercept and slope for N-back level were used to examine the effects of N-back level and diagnostic group on *d'*.

Discounting Choices

Subjective Value of Discounting Choices. Subjective value (SV) for each of the comparison N-back levels (2-, 3-, 4-back) was calculated for each high offer amount according to procedure detailed in Westbrook et al., 2013. SV was then divided against the high offer amount and this standardized SV was used throughout the analysis. A mixed-effects linear regressions with subject-level intercept and slope for N-back level was used to examine which factors affected the SV. Preliminary analysis showed that the base offer of the hard option ($2 or $5) did not alter the SV or interact with other variables. It was therefore left out of the models for the final analyses.

Diffusion Modeling of Discounting Choices. Response and RT of the discounting choices were modelled using HDDM regression models. Trials with RT faster than 300ms and slower than 3SD were excluded (Ratcliff, & Tuerlinckx, 2002).

Diffusion parameters for the N-back trials were estimated using regression models of the hierarchical Bayesian estimation of diffusion parameters (HDDMRegressor in HDDM toolbox, Wiecki et al., 2013). HDDM constrains fits of individual subjects by group distributions, producing more accurate diffusion parameter estimates when trial numbers are low (Wiecki et al., 2013). Default prior distributions were used, based on a collection of decision-making studies with best-fitting parameters (Matzke, & Wagenmakers, 2009; Wiecki et al., 2013). Twenty thousand samples were drawn from the posterior to obtain smooth parameter estimates and the final 5000 samples were retained. Bayesian hypothesis testing was performed by analyzing the probability mass of the parameter region in question (estimated by the number of samples drawn from the posterior that fall in this region; for example, percentage of posterior samples greater than zero). Statistical analysis was performed on the group mean posteriors.

The Deviance Information Criterion (DIC) was used for model comparison, where a lower DIC value is favorable, indexing better fit of the model to the data while penalizing for complexity in the addition of degrees of freedom (Frank et al., 2015). Upper and lower boundaries represent the hard task and the easy task, respectively. We constructed and compared three diffusion models using HDDM in which: 1) *v*, *a*, *t0* and *z* varied as a function of N-back level x diagnostic group interaction; 2) *v*, *a* and *t0* varied as a function of N-back level x diagnostic group interaction, but *z* varied only by diagnostic group; and 3) *v*, *t0* varied as a function of N-back level x diagnostic group interaction, but *a* and *z* varied only by diagnostic group.

Model comparison indicated that model 3 had a slightly better fit than all other models (see Table 2). A comparison of simulated data based on estimated parameters of this model and raw data indicated reasonable model fit (see Table S1).

Results

N-back Performance

Figure 1 shows the effect of N-back level on *d'* for each diagnostic group. As expected, as N-back level increased, *d'* decreased ($\beta = -0.69$, SE = 0.06, $p < 0.001$). Both descriptive and residual plots suggest a quadratic effect of N-back level on *d'* ($level^2$: $\beta = 0.25$, SE = 0.04, $p < 0.001$; level: $\beta = -1.95$, SE = 0.21, $p < 0.001$); the greatest reduction in performance accuracy was seen between the 1- to 2-back levels. There was also a main effect of diagnostic group on *d'*, in which children with ADHD had lower *d'* across the N-back levels relative to non-ADHD controls ($\beta = -0.21$, SE = 0.36, $p = 0.001$).

Effort Discounting

As expected, there was a main effect of N-back level on subjective value in which the reward value of effort decreased as task level increased ($\beta = -0.06$, SE = 0.024, $p = 0.006$; see Figure 2). There was no main effect of diagnosis or diagnosis x N-back level interaction on subjective value (*p*s ≥ 0.30; see Figure 2A and Table 3).

Drift rate (v) to choice decision slowed as the comparison N-back option increased in load level (main effect of N-back level on v, 100% of posterior < 0; see Table 3). That is, choices were easier to make if children were asked to make a decision between completing a 1- vs. 2-back (1 back for $1 or 2-back for $2?) and were harder when asked to make a decision between a 1- and 4-back (1 back for $1 or 4-back for $2?). Interestingly, even though no difference in discounting behavior was observed between groups, this slowdown in drift rate was less pronounced in children with ADHD (level x ADHD interaction on v, 97.5% of posterior > 0). There was no strong evidence for other diagnostic group effect on diffusion parameters (see Table 3 for more details).

Effort Discounting as a Function of N-back Performance

Children with ADHD performed more poorly on the N-back, so exploratory analyses were next conducted to evaluate whether effort discounting was influenced by initial N-back performance. Effort discounting was steeper for children with better performance (interaction between overall *d'* and N-back level, $\beta = -0.07$, SE = 0.03, $p = 0.03$; see Figure 2B; see Table 4 for full model results). For those with better than average performance (overall *d'* one standard deviation above the mean), one unit increase in N-back level was associated with a 0.08 unit decrease in subjective value of the hard task ($\beta = -0.08$, SE = 0.02, $p = 0.005$). In contrast, for participants who performed below average (overall *d'* one standard deviation below the mean), one unit increase in level was only associated with a 0.01 unit decrease in subjective value ($\beta = -0.01$, SE = 0.02, $p = 0.005$).

To determine why children with better performance also appeared to discount effort more as task load increased, additional diffusion models were run to explore potential difference in the decision process between children with varying N-back *d'*. Three models were compared: 1) *v*, *a*, *t0, z* all depended on *d'* x N-back level; 2) *v*, *a*, *t0* depended on *d'* x N-back level and *z* depended on *d'* only; 3) *v*, *t0* depended on *d'* x N-back level and *a*, *z* depended on *d'*. Model comparison using DIC indicated that the second model had the best model fit, and that it also had slightly better fit than the previous model with ADHD status (see Table 2). There was reasonable model fit based on comparing simulated data to raw data (see Table S2).

Drift rate (*v*) slowed, boundary (*a*) widened and non-response time (*t0*) decreased as N-back level increased, suggesting an increase in choice difficulty and response caution (main effect of level on *v*, 100% of posterior < 0; *a*, 96.8% of posterior > 0; *t0*, 94.8% of posterior < 0; see Table 4). Moreover, all of these changes were more pronounced in children with better overall performance (*d'* x N-back level interaction on *v*, 100% of posterior < 0; *a*, 96.4% of posterior > 0; *t0*, 99.1% of posterior < 0), suggesting that they were more cognizant about the choices they were making.

There was a partial overlap between children with worse N-back performance and those with ADHD. Children with ADHD were overrepresented in the low N-back performance group. With a median split of overall N-back *d'*, 29 out of 46 of children with ADHD (63%) also fell under the group with lower-than-median *d'*, while only 10 out of 32 controls (31%) were in this group.

Discussion

The cognitive effort discounting (COG-ED) task explicitly measures the subjective value of cognitive effort. It is thus a more direct measure of motivational functioning than previous studies in ADHD that relied on reward-based performance improvement. Yet, two people may reach the same discounting choices for different reasons and following different processes. Computational models of decision making such as the diffusion model take into account the speed of choices in addition to the choice. By applying diffusion model to COG-ED, we can thus delineate the nuances in the decision process that may exist between individuals.

All children showed evidence of effort discounting, i.e. stronger preference for the easy option as task load increased. There were no diagnostic-specific effects, suggesting that children with ADHD do not preferentially choose to avoid cognitive effort. However, the ability to translate those preferences and goals into action is not equivalent, and there is some evidence that this translation is more difficult for children with ADHD (Sonuga-Barke et al., 2010). Children with ADHD are known to overestimate their own performance and maintain a positive illusory bias (Owens et al., 2007). Such overly optimistic self-evaluation may in turn lead to less strategic choices, including the choice to engage in more difficult tasks, even if it is beyond their capacity to perform well. For example, during tasks of physical effort discounting, children with ADHD make similar choices to exert physical effort compared to non-ADHD controls, but later had less success in the execution of their chosen option (Winter et al., 2019).

Metacognitive monitoring of task demand refers to the ability to identify differences in task demands (Nelson, & Narens, 1990; O'Leary, & Sloutsky, 2017). The *spontaneous* ability to monitor task demand emerges around age 5-7 (Niebaum, & Munakata, 2020) and is required for a child to independently make adaptive choices between two tasks that vary in difficulty. In the current study, exploratory analyses found that children who performed better on the N-back had steeper effort discounting curves than children who made more errors, which is somewhat antithetical to what might be expected. It seems much more reasonable to assume that children who perform worse on the initial N-back task would demonstrate steeper discounting curves because of the increased difficulty they faced when completing the N-back. But, by taking a computational account that incorporates the speed of decision making, we were able to explain this apparent paradox. Among children with high accuracy, drift rate slowed and decision boundary widened as N-back level increased. That is, children with high accuracy deliberated among the choices and required more evidence to make those decisions. This indicates that they had a better or more nuanced mental representation of demand, which in turn resulted in greater consideration prior to their ultimate choice.

Decision by sampling theory argues that people form subjective values of options by comparing samples from the environment or experience, and that the range of an individual's environment or experience affects the value judgements they make (Stewart, 2009). Adults rely on prior experience to evaluate demand selection (Dunn et al., 2016), and experiences of success or failure on a task also enable the refinement of such inferences in children (Niebaum, & Munakata, 2020). So, whereas all children completed the same number of preliminary N-back trials, children who were more accurate developed a better sample of experience from which to form more reliable estimates of task demand and to draw their value judgments. This better sample of experience could also have resulted from higher level of effort engagement in these children, because performance is affected by effort exertion (Shenhav et al., 2017). Such an interpretation is supported by previous work in typically developing children which showed that the exertion of cognitive effort (as indexed by increased pupil dilation) in more difficult tasks is also predictive of greater discounting (Chevalier, 2018).

There was a notable yet incomplete overlap between children with ADHD and those with low N-back performance. Although we found no diagnostic group difference in the effort discounting curve, diffusion modelling identified a more shallow slowdown in drift among children with ADHD as N-back level increased. This suggests that at the group level, children with ADHD were less accurate in differentiating between levels of demand, which is likely related to well-documented weaknesses in the ability to identify, monitor, and learn from errors (Arnett et al., 2021; Balogh & Czobor, 2016; Huang-Pollock et al., 2014; Liotti et al., 2005; Weigard et al., 2016). More generally, the monitoring of error or conflict is essential in the engagement of cognitive control (Fischer et al., 2008; Scherbaum et al., 2011), and identifying the amount of control needed is theorized as a necessary step towards control allocation (Shenhav et al., 2021). Therefore, a reduced ability to monitor task demand and to subsequently mobilize the control mechanisms in a context-sensitive manner may better characterize ADHD-specific deficits. For example, children with ADHD do not as effectively adjust their response strategies for tasks that vary objectively in difficulty (Feldman, & Huang-Pollock, 2021a). More broadly, the contention between the ability (i.e. executive functioning or EF) vs. motivation accounts of ADHD may be misleading. While EF does explain real-life success in self-control, this effect is moderated by individual differences in control recruitment towards goal attainment (Wolff et al., 2016).

Future Studies

In COG-ED, participants made a series of hypothetical choices in the discounting phase without actually executing their choices. Thus, the current paradigm does not account for the efficiency or quality with which participants are able to translate their choices into actions. Even though those with ADHD may choose the high-effort option as frequently as controls, they may carry out their chosen task with a reduced level of efficiency (e.g. lower performance). Moving this line of inquiry further, it is important that future work measure each separately. For example, efficiency can be measured through automatically calibrating the difficulty of the task based on participant performance.

The certainty one has about the value that a specific option carries or the overall confidence in one's own choice may also impact the translation of value-based choices into actions (De Martino et al., 2013). Choice confidence, in particular, has been found to systematically vary on the individual or trait level (Zajkowski et al., 2022). Neither choice confidence nor value certainty has been extensively studied in ADHD. Although our study found that children with ADHD had difficulty in the metacognitive evaluation of task demand, this can also be a reflection of a more fundamental alternation in their value-based decision-making process (analogous to the domain-general low processing efficiency in ADHD during perceptual decision-making, see Feldman, & Huang-Pollock, 2021b). Future studies may incorporate subjective ratings of choice confidence and/or value certainty for each option into a diffusion model of preferential choices (De Martino et al., 2013; Lee, & Usher, 2021) to further examine this possibility. Additionally, our model comparison suggested that a model where response bias did not vary by task load level had better fit, likely due to the discounting choices being interleaved. Future studies may also utilize a blocked choice design (i.e. one task load per choice block) to specifically examine response bias on a trial-by-trial basis.

Conclusion

The current study found no evidence of steeper effort discounting among a well characterized group of school aged children with ADHD, indicating that increased subjective preference for demand avoidance may not explain ADHD-related behavioral deficits. However, diffusion modeling suggested that those who performed worse on the N-back (the majority of whom were identified as having ADHD) were less accurate in metacognitive monitoring of demand, which is a critical precursor for cost-benefit analyses that underlie decisions to engage cognitive control.

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Appendix

Figures and Tables

Figure 1. Performance (d’) by N-back levels and diagnostic group.

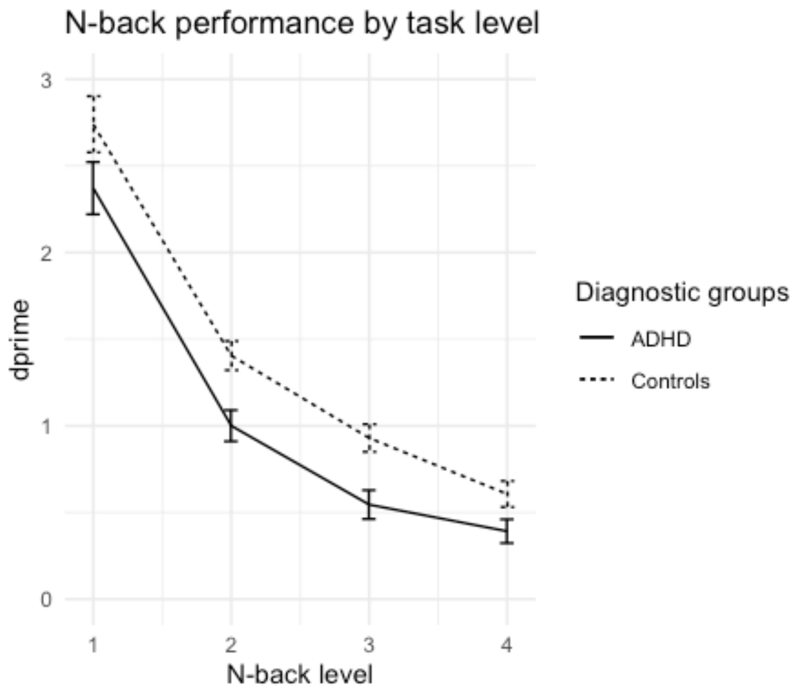

Figure 2. Effort discounting by N-back levels. Lines represent (A) diagnostic group or (B) bins based on *d'* across all N-back levels.

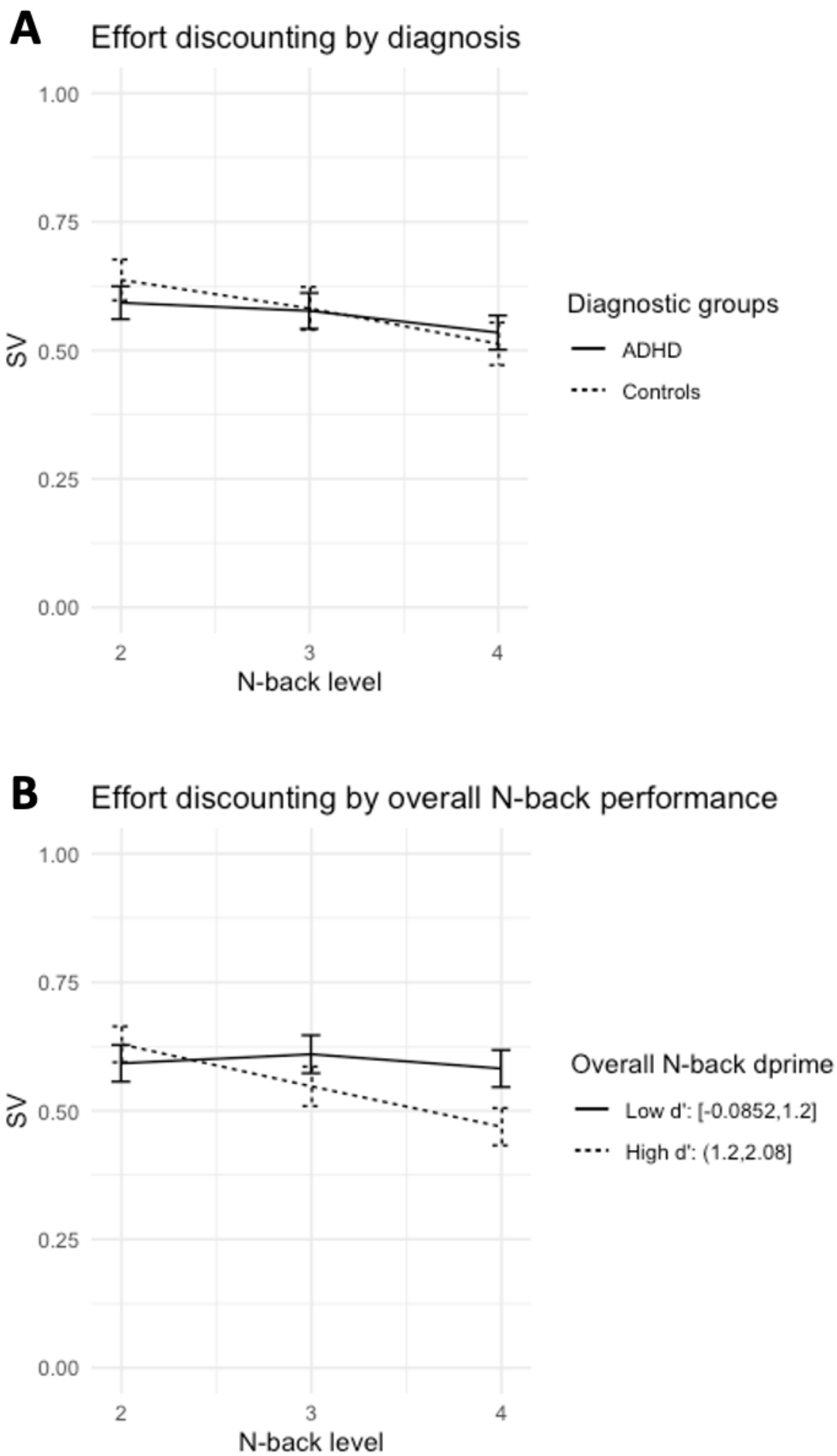

Table 1. Demographic characteristics and N-back performance by diagnostic groups.

	ADHD (n = 46)	Controls (n = 32)	F (1,76) =
Age	9.24 (1.18)	9.47 (1.14)	0.74, $p = 0.39$, $\eta^2 = 0.01$
Sex	35% female	59% female	0.26, $p = 0.61$, $\eta^2 = 0.003$
FSIQ	103 (12.88)	103 (7.35)	0.002, $p = 0.97$, $\eta^2 < 0.001$
# hyperactive symptoms	6.24 (2.71)	0.19 (0.47)	155.75, $p < 0.001$***, $\eta^2 = 0.67$
# inattentive symptoms	7.89 (1.46)	0.47 (0.72)	702.86, $p < 0.001$***, $\eta^2 = 0.90$
BASC Hyperactivity T-score			
Parent	64.72 (12.32)	43.78 (5.45)	81.13, $p < 0.001$***, $\eta^2 = 0.52$
Teacher	63.33 (13.54)	43.44 (3.56)	65.68, $p < 0.001$***, $\eta^2 = 0.46$
BASC Attention problems T-score			
Parent	64.52 (6.98)	44.44 (7.50)	147.09, $p < 0.001$***, $\eta^2 = 0.66$
Teacher	63.72 (7.28)	41.84 (5.05)	216.23, $p < 0.001$***, $\eta^2 = 0.74$
N-back			
1-back			
d'	2.37 (1.02)	2.74 (0.92)	2.67, $p = 0.11$, $\eta^2 = 0.03$
RT (sec)	0.84 (0.33)	0.77 (0.29)	77.15, $p < 0.001$***, $\eta^2 = 0.01$
2-back			
d'	1.00 (0.61)	1.40 (0.47)	9.90, $p = 0.002$**, $\eta^2 = 0.12$
RT (sec)	0.96 (0.37)	0.89 (0.33)	53.53, $p < 0.001$***, $\eta^2 = 0.007$
3-back			
d'	0.55 (0.56)	0.93 (0.45)	10.29, $p = 0.002$**, $\eta^2 = 0.12$

RT (sec)	0.84 (0.38)	0.84 (0.34)	0.42, p = 0.52, $\eta^2 < 0.001$
4-back			
d'	0.39 (0.46)	0.61 (0.42)	4.32, p = 0.04*, $\eta^2 = 0.05$
RT (sec)	0.79 (0.38)	0.78 (0.34)	1.04, p = 0.31, $\eta^2 < 0.001$

Note: mean (standard deviation in parentheses); * p< 0.05, **p< 0.01, ***p < 0.001

Table 2. Model comparison for discounting choices.

	Model specifications	DIC
ADHD as predictor	*v* ~ N-back level x ADHD, *a* ~ N-back level x ADHD, *t0* ~ N-back level x ADHD, *z* ~ N-back level x ADHD	9006.79
	v ~ N-back level x ADHD, *a* ~ N-back level x ADHD, *t0* ~ N-back level x ADHD, *z* ~ ADHD	9007.02
	v ~ N-back level x ADHD, *a* ~ ADHD, *t0* ~ N-back level x ADHD, *z* ~ ADHD	9005.06
d' as predictor	*v* ~ N-back level x overall *d'*, *a* ~ N-back level x overall *d'*, *t0* ~ N-back level x overall *d'*, *z* ~ N-back level x overall *d'*	8974.92
	v ~ N-back level x overall *d'*, *a* ~ N-back level x overall *d'*, *t0* ~ N-back level x overall *d'*, *z* ~ overall *d'*	8974.84
	v ~ N-back level x overall *d'*,	8985.22

	a ~ overall *d'*, *t0* ~ N-back level x overall *d'*, *z* ~ overall *d'*	

Table 3. Effect of N-back level and diagnostic group on subjective value (SV) using mixed effect linear regression, and on *v*, *a*, *t0, z* using HDDM regression models.

		(Intercept)	Level	ADHD	Level x ADHD
SV	Estimate	0.70 (0.06)	-0.06 (0.02)	-0.08 (0.07)	0.03 (0.03)
	p-value	NA	0.006**	0.70	0.30
v	Estimate	0.52 (0.15)	-0.16 (0.04)	-0.18 (0.20)	0.10 (0.05)
	Posterior probability	100%	100%	80.0%	97.5%
	95% CI	[0.21, 0.80]	[-0.23, -0.08]	[-0.57, 0.20]	[0.00, 0.18]
a	Estimate	2.34 (0.09)	NA	0.06 (0.11)	NA
	Posterior probability	100%	NA	70.7%	NA
	95% CI	[2.17, 2.51]	NA	[-0.16, 0.27]	NA
t0	Estimate	0.66 (0.06)	-0.01 (0.01)	-0.01 (0.07)	0.003 (0.02)
	Posterior probability	100%	74.8%	55.2%	58.7%
	95% CI	[0.55, 0.79]	[-0.03, 0.01]	[-0.14, 0.13]	[-0.03, 0.04]
z	Estimate	0.53 (0.01)	NA	-0.0003 (0.02)	NA
	Posterior probability	100%	NA	50.2%	NA
	95% CI	[0.50, 0.55]	NA	[-0.04, 0.04]	NA

Note: All coefficient estimates have SE in parentheses; * $p< 0.05$, ** $p< 0.01$, *** $p < 0.001$

Table 4. Effect of N-back level and overall N-back performance (*d'*, mean-deviated) on subjective value (SV) using mixed effect linear regression, and on *v*, *a*, *t0, z* using HDDM regression models.

		(Intercept)	Level	*d'*	Level x *d'*
SV	Estimate	0.50 (0.10)	0.04 (0.04)	0.13 (0.08)	-0.07 (0.03)
	p-value	NA	0.005**	0.80	0.029**
v	Estimate	0.42 (0.09)	-0.11 (0.02)	0.41 (0.19)	-0.20 (0.05)
	Posterior probability	100%	100%	97.9%	100%
	95% CI	[0.24, 0.61]	[-0.15, -0.06]	[0.02, 0.76]	[-0.29, -0.11]
a	Estimate	2.26 (0.08)	0.06 (0.03)	-0.39 (0.17)	0.12 (0.07)
	Posterior probability	100%	96.8%	98.9%	96.4%
	95% CI	[2.10, 2.43]	[0.00. 0.12]	[-0.71, -0.05]	[-0.01, 0.25]
t0	Estimate	0.69 (0.05)	-0.02 (0.01)	0.36 (0.08)	-0.08 (0.03)
	Posterior probability	100%	94.8%	100%	99.1%
	95% CI	[0.60, 0.79]	[-0.04, 0.00]	[0.19, 0.52]	[-0.13, 0.02]
z	Estimate	0.53 (0.01)	NA	0.02 (0.02)	NA
	Posterior probability	100%	NA	85.8%	NA
	95% CI	[0.51, 0.55]	NA	[-0.02, 0.06]	NA

Note: The estimates for the effects of Level on *a* and *z* were not shown since the fit of the model where *a* and *z* depend on Level was inferior to the current model. All coefficient estimates have SE in parentheses; * $p< 0.05$, ** $p< 0.01$, *** $p < 0.001$.

Supplementary Material

Table S1. Data simulation based on discounting model where *v*, *t0* varied by N-back level x ADHD and *a*, *z* varied by ADHD.

	Observed data	Simulated data	MSE	Within 95% credible interval
% Choice_ub	0.59	0.59	0.06	TRUE
RT Mean_ub	1.76	1.92	0.55	TRUE
RT SD_ub	1.05	0.94	0.24	TRUE
RT 10q_ub	0.73	1.06	0.34	TRUE
RT 30q_ub	1.10	1.33	0.34	TRUE
RT 50q_ub	1.46	1.66	0.47	TRUE
RT 70q_ub	2.05	2.13	0.72	TRUE
RT 90q_ub	3.30	3.07	1.60	TRUE
RT Mean_lb	2.14	2.06	0.61	TRUE
RT SD_lb	1.13	0.94	0.34	TRUE
RT 10q_lb	0.83	1.20	0.42	TRUE
RT 30q_lb	1.43	1.47	0.35	TRUE
RT 50q_lb	1.95	1.80	0.52	TRUE
RT 70q_lb	2.56	2.28	0.88	TRUE
RT 90q_lb	3.73	3.19	2.15	TRUE

Note: All RTs are in seconds. ub: upper boundary, i.e. the hard option; lb: lower boundary, i.e. the easy option. MSE (mean-squared error) is a measure of how close in value the summary statistic of the observed data is from that of the simulated data.

Table S2. Data simulation based on discounting model where *v*, *a*, *t0* varied by N-back level x overall *d'* and *z* varied by overall *d'*.

	Observed data	Simulated data	MSE	Within 95% credible interval
% Choice_ub	0.59	0.59	0.06	TRUE
RT Mean_ub	1.76	1.91	0.55	TRUE
RT SD_ub	1.05	0.93	0.25	TRUE
RT 10q_ub	0.73	1.06	0.34	TRUE
RT 30q_ub	1.10	1.32	0.35	TRUE
RT 50q_ub	1.46	1.63	0.46	TRUE
RT 70q_ub	2.05	2.11	0.71	TRUE
RT 90q_ub	3.30	3.05	1.61	TRUE
RT Mean_lb	2.14	2.06	0.63	TRUE
RT SD_lb	1.13	0.95	0.36	TRUE
RT 10q_lb	0.83	1.19	0.39	TRUE
RT 30q_lb	1.43	1.46	0.35	TRUE
RT 50q_lb	1.95	1.79	0.52	TRUE

RT 70q_lb	2.56	2.27	0.91	TRUE
RT 90q_lb	3.73	3.20	2.29	TRUE

Note: All RTs are in seconds. ub: upper boundary, i.e. the hard option; lb: lower boundary, i.e. the easy option.