#### Cognitive deficits and enhancements in youth from adverse conditions: An integrative assessment using Drift Diffusion Modeling in the ABCD study

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#### This work was supported by XXX. We declare no conflicts of interest. All scripts and materials (including instructions for how to reproduce the findings) are available on the GitHub repository [(https://github.com/StefanVermeent/abcd\_ddm)](https://github.com/StefanVermeent/abcd_ddm) Correspondence concerning this article should be addressed to Stefan Vermeent, Utrecht University, Department of Psychology, Heidelberglaan 1, 3584 CS, Utrecht, The Netherlands, E-mail: p.c.s.vermeent@uu.nl

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# Introduction

The effects of adverse experiences—such as growing up in poverty or experiencing high levels of violence—on cognition are complex. For example, the deficit approach shows that growing up in adverse conditions tend to have detrimental effects, such as impairing learning and memory (Sheridan et al., 2022; Sheridan & McLaughlin, 2014). In contrast, the adaptation-based approach suggests that people’s cognitive abilities are tailored to challenges in the environment, helping people solve real problems in everyday life (Ellis et al., 2022; Frankenhuis et al., 2016; Frankenhuis & Weerth, 2013). Combining these approaches, adversity might enhance abilities that help solve real challenges but reduce abilities that do not. Both approaches are valid and integrating over their complimentary insights will help the field draw a high-resolution map of adversity-effects (Frankenhuis & Weerth, 2013).

Yet, before we can can integrate findings and build solid theory, two methodological issues common to both approaches need to be addressed. First, most studies measure cognitive abilities using raw performance indicators, such as response times (RT) and/or accuracy. Whether implicitly or explicitly, researchers often assume these indicators reflect only variation in ability. However, this is rarely the case. For example, consider a basic cognitive task, such as judging whether a shape is a square or a triangle. An associated raw RT captures several sequential processing stages. The participant must visually encode the shape, sample information, and execute a response (Forstmann et al., 2016; Lo & Andrews, 2015; Posner, 2005; Ratcliff & McKoon, 2008; Sternberg, 1969). Any difference in raw RT could occur at any of these stages, which have different implications for inferences about cognitive abilities. The second problem is that studies tend to ignore how abilities are related and either look at individual tasks in isolation or collapse performance across tasks (e.g., by creating a single executive functioning composite score). However, different cognitive tasks are not fully independent; performance on any cognitive task likely reflects both task-specific processes (e.g., shifting ability on an attention shifting task, working memory updating on an n-back task) as well as processes that are shared across tasks (Lerche et al., 2020).

In this paper, we simultaneously address both of these methodological challenges. First, we use modern cognitive modeling that formalizes the stages of processing underlying RT and accuracy. Second, we leverage analytic methods that can distinguish unique and specific abilities (e.g., attention-shifting or inhibition) from general abilities common to most tasks (e.g., general cognitive efficiency).

## Do deficit and enhancement patterns mean what we think they mean?

Both the deficit and adaptation literature use speeded tasks, in which responses must be both fast and accurate. For example, performing well on inhibition tasks [e.g., Flanker task, go-no go task; Farah et al. (2006); Fields et al. (2021); Mezzacappa (2004); Noble et al. (2005)], attention shifting tasks [e.g., Dimensional Change Card Sort; Farah et al. (2006); Fields et al. (2021); Young et al. (2022); Mittal et al. (2015); Noble et al. (2005)], and stimulus detection tasks (Farah et al., 2006; Noble et al., 2005; Pollak, 2008) requires fast and accurate responses. But in practice, performance is often quantified using speed alone (e.g., RT), accuracy alone (e.g., proportion correct), or both independently (rather than in an integrated manner). This is problematic because raw RT or proportion correct scores do not capture how speed and accuracy trade off with each other. This tradeoff holds information about each stage of cognitive processing involved in executing a task. Thus, relying on raw performance indicators alone may hide adversity-related performance differences, or perhaps worse, lead us to infer a cognitive deficit or enhancement when none might exist.

The good news is that cognitive science includes well-established frameworks for quantifying tradeoffs between speed and accuracy. For speeded tasks, a popular measurement model is the Drift Diffusion Model [DDM; Forstmann et al. (2016); Ratcliff & Rouder (1998); Ratcliff & McKoon (2008); Wagenmakers (2009)]. The DDM integrates speed and accuracy on a trial-by-trial level to estimate what happens at different stages of cognitive processing. It can be fitted to tasks that require people to quickly choose between two response options.

To illustrate, imagine a task where participants are instructed to indicate whether two images are the same or different. If it is the same, they press the left-arrow key, and if they are different they press the right-arrow key.

DDM assumes that people go through three distinct phases of cognitive processing on each trial (see Figure 1). The first phase is *preparation*, which includes processes like focusing attention and visually encoding the stimulus. Second, they enter the *decision* phase. During this phase, people gather evidence for both response options (are the images the same or different). Third, once the evidence sufficiently favors one option over the other (explained below), the decision-process terminates and the corresponding response is executed.

DDM captures the decision phase using a *random walk* process that drifts towards one of two *decision boundaries*. The upper boundary corresponds to the correct response, whereas the lower boundary corresponds to the incorrect response. Information samples collected at each timepoint can cause the process to move towards the upper boundary (leading to a correct response) or towards the lower boundary (leading to an incorrect response). The DDM assumes information samples are noisy, and so people sometimes make mistakes (i.e., reach the lower decision boundary), even on simple tasks.

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| **Figure 1.** A visual overview of the Drift Diffusion Model (DDM). The DDM assumes that decision-making on cognitive tasks with two forced response options advances through three stages: First, people go through a preparation phase in which they engage in initial stimulus encoding. Second, people gather information for one of two response options. Each jiggly line represents the evidence accumulation process on a single trial. Third, when the accumulation process terminates at one of the decision boundaries, a motor response is triggered in the execution phase. The model estimates four parameters that reflect distinct cognitive processes (printed in italic): 1. The **drift rate** represents the rate at which evidence accumulation drifts towards the decision boundary and is a measure of processing speed. 2. The **non-decision time** represents the combined time spent on task preparation and response execution. 3. The **boundary separation** represents the width of the decision boundaries and is a measure of response caution. 4. the **starting point** represents the starting point of the decision process and can be used to model response biases. |

DDM estimates a set of parameters for each participant that map onto distinct cognitive processes (Voss et al., 2004). The *drift rate* represents the speed of information processing (Schmiedek et al., 2007; Voss et al., 2013). People with a higher drift rate are faster and make fewer errors. The *non-decision time* includes initial preparatory processes such as visually encoding the stimulus and processes after the decision is made, such as the motor response (e.g., pressing a button). All else being equal, longer non-decision times reflect slower processing but without a cost nor benefit in accuracy. However, for complex tasks, the non-decision time may capture other processing required to execute a task. Examples are the time taken to rotate an image on a mental rotation task (Feldman & Huang-Pollock, 2021), filtering out distracting information on a Flanker task (Ong et al., 2017), and updating task rules held in working memory (Schmitz & Voss, 2012, 2014). The *boundary separation* represents the distance between the two decision boundaries. A larger boundary separation means more information is required to make a decision. In contrast to non-decision time, larger boundary separation leads to slower but more accurate responses. In effect, it captures the speed-accuracy tradeoff. Finally, the *starting point* can be used to model a person’s initial bias towards one of the two decision options (e.g., a tendency to classify facial expressions as angry that extends to neutral faces).

Although there are studies that focus on changes in DDM parameters in the context of situational threats and anxiety (e.g., McFadyen et al., 2022; Thompson & Steinbeis, 2021; Tipples, 2018), no such studies exist—to our knowledge—in the childhood adversity literature. At the same time, many of the cognitive measures used in this literature rely on speed and/or accuracy. For example, physically abused youth were faster and more accurate at detecting angry faces compared to happy faces (Gibb et al., 2009; Pollak et al., 2009; Pollak, 2008). This finding could reflect several things. One interpretation is that abused youth can process angry faces more efficiently (i.e., a drift rate interpretation). Alternatively, it might reflect a response bias towards angry faces (i.e., a starting point interpretation). Finally, it could reflect a more complex combination of changes, such as a higher efficiency in processing angry faces coupled with more cautious responding (i.e., higher drift rate *and* larger boundary separation).

The same issues apply to recent studies suggesting that adverse experiences affect executive functions in different ways. For example, there is some evidence that people who grew up in unpredictable environments are faster at shifting their attention (Fields et al., 2021; Mittal et al., 2015; but see Young et al., 2022). This interpretation usually rests on a RT difference score between repeat trials (using the same classification rule as on the previous trial) and switch trials (switching to another rule). Importantly, incorrect trials are typically discarded in this procedure. Similarly, adversity exposure is typically associated with lowered inhibition (Farah et al., 2006; Fields et al., 2021; Mezzacappa, 2004; Noble et al., 2005) as indicated by slower RTs when distractors are present compared to when there are no distractors. Thus, work in the adversity literature has relied on speed and/or accuracy, but not their integration. It is therefore an open question how childhood adversity shapes different stages of processing.

## Are deficit and enhancement patterns task-specific or task-general?

An additional advantage of the DDM is that it is general; it makes few assumptions and is therefore applicable to a wide range of cognitive tasks (so long as they have some basic properties; Voss et al. (2013)). In fact, the DDM was originally developed for basic perceptual tasks (Ratcliff & Rouder, 1998; Wagenmakers, 2009), but recent studies show that it can be applied to more complex tasks as long as the task requires a single decision process (Lerche et al., 2020). Thus, the general properties of DDM allow a direct comparison of drift rates, non-decision times, and boundary separation across a wide range of tasks (e.g., inhibition, attention shifting, working memory updating, visual processing).

Several previous studies have shown that DDM parameters of executive functioning tasks reflect both task-general and task-specific processes. For example, it is well-known that RTs on executive functioning tasks are substantially confounded with general processing efficiency (Frischkorn et al., 2019; Lerche et al., 2020; Löffler et al., 2022). Lerche et al. (2020) found that covariances between drift rates were stronger for tasks with the same content domain (numerical, figural, verbal). Some recent studies even suggest that drift rates of executive tasks reflect *only* processing speed, and that after accounting for task-general processes little remains that can be attributed to task-specific abilities (Löffler et al., 2022). These findings tie in to a broader literature in cognitive science that questions the psychometric properties of many common measures of executive functioning (e.g., Bastian et al., 2020; Draheim et al., 2021, 2019; Rouder & Haaf, 2019). Although this is an ongoing debate in the cognitive literature, it is clear that accounting for task-general processes is critical if we want to assess the effect of adverse experiences on specific abilities.

Accounting for task-general processes on a latent level using SEM yields more precise estimates of task-specific processes. Imagine comparing the drift rates between an attention-shifting and a Flanker task. Drift rates of both tasks will rely for a large part on a person’s general processing efficiency since both require the rapid processing of visual information (Lerche et al., 2020; Löffler et al., 2022; Schubert et al., 2016). After accounting for this shared variance, the remaining unique task variance is thought to reflect processes that are specific to the task. For the attention shifting task, this might be how effectively the switch from one classification rule (e.g., based on color) to the other (e.g., based on shape) was made (Schmitz & Voss, 2012, 2014). For the Flanker task, it might be the speed with which attention narrows down on the target arrow (White et al., 2011; White & Curl, 2018). It is important to be able to separate between specific abilities and general processes, both for our theories about deficits (e.g., does adversity impair broad domains such as memory and learning, or does it impair processing of specific types of information, such as verbal information?), adaptations (does environmental unpredictability lead to specialized attention shifting skills?) and for real-world interventions based on those theories (e.g., if a school-based learning intervention is designed to target the specific ability).

## The current study

In this study, we will use the Adolescent Brain Cognitive Development (ABCD) study data <http://abcdstudy.org> to map adversity to general and task-specific DDM parameters of four cognitive tasks. The ABCD study is ideal because it provides a large, representative, and diverse sample of 9- to 10 year-olds. The dataset contains several measures of developmental exposure to threat and deprivation and several well-known cognitive tasks.

Here, we focus on four tasks measuring processing speed, attention shifting, inhibition and mental rotation. Some previous work found evidence for an enhanced attention shifting ability in people who grew up in an unpredictable environment Young et al. (2022), whereas inhibition is typically found to be impaired as a result of adverse experiences (e.g., Farah et al., 2006; Fields et al., 2021; Mezzacappa, 2004; Noble et al., 2005). However, the decision for these four tasks was primarily guided by the fact that they adhered to the assumptions of the DDM, and to a lesser extent by previous empirical findings. Given that we currently do not know enough about performance differences at different stages of cognitive processing, we believe an important first step is to do robust and informed exploratory work by systematically comparing across a diverse set of abilities.

The DDM has yet to be systematically applied to deficit and enhancement research and holds promise for two reasons. First, DDM can identify *where* a deficit or enhancement manifests in the stages of cognitive processing. Second, we can estimate whether deficits and/or enhancements are *task-general* or *task-specific* (e.g., Lerche et al., 2020; Löffler et al., 2022; Schubert et al., 2016). We will do so by using SEM to leverage DDM and separate unique and shared variance across tasks. First, we will estimate shared processes for each DDM parameter (i.e., drift rate, boundary separation, and non-decision time) on a latent level. When applied to the drift rate, for example, such a latent factor would capture general cognitive efficiency that plays a role across all tasks. After accounting for shared variance, the task-specific variance that remains (i.e., the *residual variance*) reflects variance unique to each task. We then estimate the association of several dimensions of adversity with both the general (latent) factor and specific (residual) task variance (See Figure 2 for a visualization). By leveraging DDM and SEM together, we can identify nuanced patterns of cognitive processing from which we can build more solid theories about the effect of adversity on cognition.

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| **Figure 2.**. Structural Equation Modeling visualization of the model. Squares represent manifest variables; Ellipses represent latent variables; dashed lines represent factor loadings; thick black lines represent the regression paths of interest. For reasons of model identification, the loading of the general factor on Processing Speed is fixed to 1, and no regression path is estimated between adversity and the unique variance of Processing Speed. The latent factors denoted with U represent the residual variances of DDM parameters after accounting for shared variance on the latent level. This can be achieved by fixing their factor loadings to 1, and by fixing the variances of the manifest DDM parameters to 0. |

# Methods

## Sample

This study will be based on the baseline cohort of the ABCD study (<http://abcdstudy.org>; Data Release 4.0), which is a prospective, longitudinal data collection focused on brain development and child health in the United States. At baseline, the study included 11,878 youths (between 9 and 10 years of age) recruited across 21 sites using multi-stage probability sampling in order to obtain a nationally representative sample. Baseline assessments were completed between September 1st 2016 and August 31st 2018. For more information about sampling procedures, see Garavan et al. (2018). We will limit our analyses to the baseline assessments as these include the largest collection of cognitive tasks suitable for DDM (Luciana et al., 2018).

Cognitive summary scores were available for 11,876 participants. Of these, we were unable to recover the data of 1,189 participants due to unrecoverable typos in the participant IDs of the trial-level data and due to an unresolved issue in ABCD Data Release 4.0 causing missing data for two sites. Thus, we included *N* = 10,687 participants who had data available on all four^1. cognitive tasks.

### Open Science Statement

All scripts and materials as well as detailed instructions necessary to reproduce the findings can be found on the article’s Github repository [(https://github.com/stefanvermeent/abcd\_ddm)](https://github.com/stefanvermeent/abcd_ddm). The raw study data cannot be shared on public repositories. Thus, to fully replicate our findings, personal access to the ABCD dataset is required <https://nda.nih.gov>. To allow computational reproducibility of the analyses, synthetic data files will be provided which can be used as input to the analyses scripts. Note that these will return different results than those reported in the article.

We obtained access to the full ABCD data repository and performed initial data cleaning and analyses *prior* to stage 1 submission. However, we only did so focusing on the cognitive task data in isolation to prevent biasing our substantial analyses. The goal of these analyses was to assure that the pre-selected cognitive tasks adhered to basic DDM assumptions and had the required trial-level data available in the right format. These initial analyses were [preregistered](https://github.com/StefanVermeent/abcd_ddm/blob/main/preregistrations/2022-09-20_preregistration_DDM.md).

Importantly, by only looking at the cognitive task data in isolation, we did not bias our substantive analyses. To increase transparency, we developed a workflow in R that tracked the data files that were loaded into the analysis environment. If a data file had not been previously accessed, this triggered an automatic commit of this information to the online GitHub repository. See the supplemental materials for a detailed description and visual overview of this workflow. An overview of the data access history is provided in the repository’s README file.

## Exclusion Criteria

For the cognitive task data, we [preregistered](https://github.com/StefanVermeent/abcd_ddm/blob/main/preregistrations/2022-09-20_preregistration_DDM.md) several exclusion criteria, first cleaning the trial-level data and subsequently applying case-wise exclusions. First, we removed RTs of the Attention Shifting, Flanker, and Mental Rotation Tasks exceeded the build-in response time-out of these tasks (0.07%, 0.04%, and < 0.01% of trials, respectively). The Processing Speed did not have a programmed time-out, but we decided to cut-off responses > 10 s (0.15% of trials) to remove extreme outliers. This step was not preregistered as we did not anticipate these extreme outliers.

Next, we removed trials with: 1) RTs < 300 ms (ranging from 0.01% to 1.03% of trials across tasks); 2) response times > 3 *SD* above the intra-individual mean of log-transformed RTs (ranging from 0.02% to 0.85% of trials across tasks); 3) trials with missing response times and/or accuracy data (< 0.01% for all tasks except Mental Rotation, see below).

Some additional trial-level decisions were not preregistered. We found that the 5 s response time-out on the Mental Rotation Task led to missing responses on 10.55% of trials which truncated the tail of the RT distribution. As this can bias DDM parameter estimation, we decided to impute these values instead of removing them (see the Methods section). In addition, for the Processing Speed task we removed trials < 3 *SD* below the intra-individual mean of log-transformed RTs to get rid of a number of fast outliers (0.22%). Fast outliers are particularly problematic for DDM because they can substantially bias parameter estimation (REF).

Next, we excluded participants who 1) had suffered possible mild traumatic brain injury or worse (*n* = 118); 2) showed a response bias of > 80% on two or more tasks (*n* = 0); 3) had a low number of trials left after trial-level exclusions, defined as 20 trials for Mental Rotation and Attention Shifting (*n* = 113 and 19, respectively) and < 15 trials for Flanker and Processing Speed (*n* = 64 and 34, respectively). Finally, we excluded one participant with 0% accuracy on the Processing Speed Task and one participant with 0% accuracy on the Mental Rotation Task.

Some of the case-wise exclusions deviated from the preregistration. We planned to exclude participants who performed at chance level, but we later learned that this was not necessary for the DDM (the DDM can handle performance at or below chance) and would lead to the exclusion of a substantial part of the sample. In addition, we planned to use 20 trials as the cut-off for all tasks, but this turned out to be an overly strict criterium for the Processing Speed and Flanker Task. Finally, we ended up not excluding participants with missing data one one or more tasks, as the main analyses can account for missing data points.

The final sample consisted of 10,563 participants.

## Measures

### Cognitive Tasks

**Flanker Task.** The NIH Toolbox Flanker task is typically used as a measure of cognitive control and attention (Zelazo et al., 2014). Participants are presented with five arrows that are positioned side-by-side. The four flanking arrows always point in the same direction, either left or right. The central arrow either points in the same direction (12 congruent trials) or in the opposite direction (8 incongruent trials). The participants are instructed to always ignore the flanking arrows and push a button to indicate whether the central arrow is pointing left or right.

**Processing Speed Task.** The NIH Toolbox Pattern Comparison Processing Speed task (Carlozzi et al., 2015) is a measure of visual processing. On each trial, participants are presented with two images and have to decide whether the images are the same or different. When images are different, they vary on one of three dimensions: color, adding or taking something away, or containing more or less of a particular item. Participants have 90 s to complete as many trials as possible.

**Attention Shifting Task.** The NIH Toolbox Dimensional Change Card Sort Task is a measure of attention shifting, sometimes also broadly construed as cognitive flexibility (Zelazo et al., 2014; Zelazo, 2006). At the bottom of the screen, participants see an image of a white rabbit and a green boat. On each trial, a third object is presented at the center of the screen that they have to match either by shape or by color with the two images below. After XXX practice trials, participants first go through a block of trials where they only have to sort based on one dimension, after which they go through second block of trials where they have to switch to the other dimension. Finally, they perform a final block of trials where they have to alternate between dimensions in pseudo-random order. All participants were presented with 23 “repeat” trials (i.e., the sorting rule is the same as on the previous trial) and 7 “switch” trials (i.e., the sorting rule is different than on the previous trial).

**Mental Rotation Task.** The Little Man task (referred to in this article as the Mental Rotation task) is a measure of visual-spatial processing (Luciana et al., 2018). Participants see a rudimentary image of a male figure holding a briefcase in his left or right hand. Participants have to indicate whether the the briefcase is in the left or right hand using corresponding buttons. The image can be presented in four different orientations: right side up versus upside down and facing the participant versus facing away. Thus, on half of the trials, participants have to mentally rotate the image in order to make the decision. Participants first go through XXX practice trials and then complete 32 test trials.

### Adversity measures

**Material deprivation.** Seven items from the parent-reported ABCD Demographics Questionnaire will be used to assess material deprivation. These items originate from the Parent-Reported Financial Adversity Questionnaire (PRFQ; Diemer et al., 2013). The items assess whether or not (1 = Yes, 0 = No) the child’s family experienced several economic hardships over the 12 months prior to the assessment (e.g., ‘Needed food but couldn’t afford to buy it or couldn’t afford to go out to get it’).

**Threat exposure.** Threat experienced in the youth’s home will be assessed using the Family Conflict subscale of the ABCD Family Environment Scale [FES; Moos (1994); Zucker et al. (2018)]. The FES consisted of 9 items assessing conflict with family members (e.g., ‘We fight a lot in our family’). Items were endorsed with either 1 (True) or 0 (False). Two items are positively valenced and will therefore be reverse-scored.

**Violence exposure.** The level of violence exposure of the child will be assessed using two questionnaires. First, we will use the parent-reported neighborhood safety/crime questionnaire including three items: 1) ‘I feel safe walking in my neighborhood’; 2) ‘Violence is not a problem in my neighborhood’; 3) ‘My neighborhood is safe from crime’ (Toolkit, 2016). Neighborhood was defined as the area within about a 20-minute walk of the child’s home, and items were endorsed on a scale of 1 (Strongly disagree) to 5 (Strongly agree).

Second, we used the parent-reported diagnostic interview for DMS-5 relating to traumatic events (Clark et al., 2010). Items assessed whether or not (1 = True; 0 = False) the child had experienced several events (e.g., ‘Witnessed someone shot or stabbed in the community’).

## Proposed Analysis Pipeline

### Initial Analyses (Prior to Stage 1 Submission)

See Table 1 for an overview of mean RTs and accuracy for all cognitive tasks.

[Add simulation results later].

**Table 1.** Descriptive statistics of mean RTs and accuracy for the cognitive tasks

|  | RT Mean (SD) | Accuracy Mean (SD) | Accuracy Min | Accuracy Max |
| --- | --- | --- | --- | --- |
| Processing Speed | 2.24 (0.47) | 96.39 (4.44) | 38.89 | 100 |
| Flanker | 0.91 (0.33) | 99.31 (3.25) | 52.63 | 100 |
| Mental Rotation | 2.65 (0.47) | 65.88 (17.91) | 6.9 | 100 |
| Attention Shifting | 1.01 (0.35) | 92.62 (8.14) | 18.52 | 100 |

### Planned main analyses

All analyses will be done using R. For the main analyses, we will split the full sample up in a training set (*n* = 1,500) and a test set (*n* ~= 8,500). First, the DDM will be fit to the cognitive task data of the training set using the *hBayesDM* package (**ahm\_2017?**). Second, we will fit several SEM models to the training set to estimate the effect of different dimensions of adversity on task-specific and task-general variance of DDM parameters using the *blavaan* package (Merkle et al., 2021). Finally, we will do an out-of-sample validation of the estimated SEM models on the test set to investigate the robustness of the effects of adversity on different stages of processing.

**Step 1: DDM estimation.** The DDM will be fit to each cognitive task in a hierarchical Bayesian framework which estimates DDM parameters both on the individual and group level (Vandekerckhove et al., 2011; Wiecki et al., 2013). The benefit of this approach is that parameter estimates of individual participants are informed and constrained by the group-level estimates. This is contrary to classic frequentist approaches to DDM estimation where the model gets fitted to the data of each participant separately (Voss et al., 2013). Thus, the model capitalizes on information available in the full sample, requiring fewer trials per participant (Lerche et al., 2017). This is useful in developmental samples like the ABCD dataset which tend to have few trials per participant but substantially larger sample sizes than is typical in the DDM literature.

See the supplemental materials for more information about model specification, estimation, and assessment. All models will freely estimate the drift rate, non-decision time, and boundary separation while constraining response bias to 0.5 (i.e., assuming no bias towards a particular response option). For the Flanker and Attention Shifting Task, we will compare model versions that separately estimate drift rate and non-decision-time per condition (congruent vs. incongruent and switch vs. repeat trials, respectively) or collapse across conditions. Boundary separation will be constrained to be the same across conditions. This assumes that people are unable to change their response strategy (i.e., move their decision boundaries) between trials when they cannot anticipate the condition of the next trial. The best-fitting model of each task will be used to estimate participant-level DDM parameters.

**Step 2: SEM estimation.** Next, we will construct several Bayesian SEMs based on the training set, all with the same basic structure (See Figure 2, step 2). Each SEM will consist of a latent measurement model and a structural model specifying the regression paths of interest. The latent measurement model of each SEM will consist of the estimates of a particular DDM parameter across all tasks (e.g., all drift rates) loading on a single latent factor. To identify the model, the factor loading on the DDM estimate of the Processing Speed Task will be fixed to 1. Unique (residual) variances of the manifest DDM parameters will be captured in additional latent factors (one per parameter). To achieve this, these factor loadings will be fixed to 1, and the variances of the manifest variables will be fixed to 0.

The structural part of the model involves the estimated regression pathways going from each adversity measure (see [Adversity measures](#meth_adversity)) to the general latent factor and to the unique variances of the DDM parameters of the Attention Shifting, Flanker, and Mental Rotation Task. We do not estimate a regression path to the unique variance of the Processing Speed Task because the model would not be identified. Thus, the Processing Speed Task serves mostly as a baseline measure to scale the general latent factor.

Goodness-of-fit will be assessed using Bayesian analogs of the following frequentist fit statistics: The root mean square error of approximation (RMSEA) and the comparative fit index (CFI) (Garnier-Villarreal & Jorgensen (2020)). In line with Hu & Bentler (1999), CFI values > .90 and RMSEA values < .08 will be interpreted as acceptable model fit and CFI values > .95 and RMSEA values ≤ .06 as good model fit. In case of bad model fit, we use the training set to explore alternatives in a data-driven manner. The robustness of the SEM findings (with and without potential changes to the model structure) will be tested in the test set in step 3.

**Step 3: Out-of-sample validation.**

TBD

# Footnotes

^1 The preregistration also included the Picture Vocabulary Task. However, after accessing the data we realized that this task was implemented using computerized adaptive testing (Luciana et al., 2018). This makes it unsuitable for DDM, as the model assumes the level of difficulty is the same across trials.

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