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# Improving Neurocognitive Testing Using Computational Psychiatry—A Systematic Review for ADHD

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Computational models, in conjunction with (neuro)cognitive tests, are increasingly used to understand the cognitive characteristics of participants with attention-deficit/hyperactivity disorder (ADHD). We reviewed 50 studies from a broad range of cognitive tests for ADHD to synthesize findings and to summarize the new insights provided by three commonly applied computational models (i.e., diffusion decision models, absolute accumulator models, ex-Gaussian distribution models). Four areas are discussed to improve the utility of (neuro)cognitive testing for ADHD: (a) the requirements for appropriate application of the computational models; (b) the consideration of sample characteristics and neurophysiological measures; (c) the integration of findings from cognitive psychology into the literature of cognitive testing to reconcile mixed evidence; and (d) future directions for the study of ADHD endophenotypes. We illustrate how computational models refine our understanding of cognitive concepts (slow processing speed, inhibition failures) presumed to characterize ADHD. We also show that considering sample characteristics and integrating findings from computational models and neurophysiological measures provide evidence for ADHD endophenotype-specific cognitive characteristics. However, studying the cognitive characteristics of ADHD endophenotypes often lies beyond the scope of existing research for three reasons: some cognitive tests lack sensitivity to detect clinical characteristics; analysis methods do not allow the study of subtle cognitive differences; and the precategorization of participants restricts the study of symptom severity on a continuous spectrum. We provide recommendations for cognitive testing, computational modeling, and integrating electrophysiological measures to produce more valuable tools in research and clinical practice (above and beyond the research domain of ADHD).

***Public Significance Statement***
Neurocognitive testing lacks evidence-based standards on tasks and methods used. This review of research on attention-deficit/hyperactivity disorder (ADHD) shows that studies are often not comparable because of differences in tasks, participant groups, and provided performance measures. We suggest that sequential sampling models are promising tools to advance research in this domain, but common tests need adaptations to improve our understanding of differences and similarities between various ADHD endophenotypes and frequently co-occurring diagnoses.

*Keywords:* ADHD endophenotypes, cognitive tests, computational decision models, computational psychiatry, neurocognitive testing



Attention-deficit/hyperactivity disorder (ADHD) is a widespread disorder that includes symptoms of inattention, impulsivity, and hyperactivity. The current *Diagnostic and Statistical Manual of Mental Disorders* (*DSM–5*; American Psychological Associa-

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tion, 2013) distinguishes among three ADHD presentations, namely the predominantly inattentive-type (ADHD-I); the predominantly hyperactive presentation (ADHD-H); and the combined presentation (ADHD-C), which shares characteristics of the other two (i.e., ADHD-I, ADHD-H). We subsequently refer to these three presentations as subtypes.

There is a common acknowledgment that most participants with ADHD experience a diverse range of symptoms with disparate severity (Kofler et al., 2019; Mostert et al., 2015; Sjöwall & Thorell, 2019; Wåhlstedt et al., 2009; Willoughby et al., 2019). A growing body of research also suggests that comorbidities frequently accompany ADHD, such as anxiety, depression, bipolar disorder, autism spectrum disorder, obsessive–compulsive disorder, and oppositional defiant disorders (Avila et al., 2004; Becker et al., 2015; Birmaher et al., 2006; Nikolas et al., 2019; Singh et al., 2006; Spencer et al., 1999). These comorbidities themselves potentially have unique cognitive characteristics that may interact with or mask characteristics specific to ADHD. Therefore, researchers and clinicians are searching for features that characterize ADHD and for procedures to diagnose different ADHD endophenotypes[1] (e.g., Becker et al., 2015; Coghill et al., 2005; Killeen, 2019; Nigg, 2001, 2005; Vaurio et al., 2009).

Identifying the cognitive characteristics of ADHD endophenotypes may help in the selection of effective treatments by tailoring them to the specific demands of the different endophenotypes (Kofler et al., 2017, 2013; Nigg et al., 2005). Given that approximately one-third of participants with ADHD do not sufficiently respond to medical treatments, finding and tailoring effective treatments is important (Adler et al., 2006; Bhandary et al., 1997; Levy, 2009). Moreover, some studies have shown that certain endophenotypes (e.g., ADHD with comorbid anxiety) respond differently to medical interventions than do others (Jensen et al., 2001; MTA Cooperative Group, 1999; Pliszka, 1989).

The diagnosis of ADHD requires the exclusion of other disorders as the best explanation of the symptoms. Diagnosis is often based on multiple measures such as participant clinical interviews and behavioral questionnaires (e.g., The Conners-3 Parent and Teacher scales, Conners, 2008; The Wender Utah Rating Scale, Ward et al., 1993). Also, attempts have been made to complement these diagnostic measures with (neuro)cognitive testing[2] (Doyle et al., 2000; Nigg, 2001).

## The Importance of Understanding Cognitive Characteristics of ADHD Endophenotypes

We discuss three reasons why a better understanding of particular *cognitive* characteristics of ADHD endophenotypes using model-based analyses is important:

### *Reason 1: ADHD Endophenotypes May Have Unique Signatures in Distinct Components of the Decision Process*

ADHD endophenotypes may express unique characteristics in distinct components of their decision process, which can be studied in cognitive tasks. By so doing, researchers can examine how participants trade-off between making accurate versus fast decisions, the extent to which they rely on a priori beliefs rather than presented information (e.g., beliefs about what type of stimulus is presented next), or the quality of information integration on which they base their decisions. Applying sequential sampling models (described in the Method section) to data from cognitive tasks allows the decomposition of the test performance (which are a result of latent decision processes) into distinct cognitive components that can be separately examined. These distinct cognitive components do not have a 1:1 correspondence with either reaction time (RT) or accuracy, but they transform these data into the components. Moreover, sequential sampling models may serve as an instrument to characterize and study different ADHD endophenotypes. For instance, White et al. (2010a) applied a model analysis to the data from a recognition memory task. They found that participants with high-trait anxiety scores had slower responses than participants with low-trait anxiety scores not because of slow processing speed, but because the participants with high-trait anxiety scores required more information to make a response (i.e., more cautious response strategy) than did participants with low-trait anxiety scores (i.e., less cautious response strategy). A pronounced cautiousness in response strategy may also be a characteristic of participants with ADHD and comorbid anxiety.

### *Reason 2: Cognitive Components May Be Informative Beyond Cognitive Tests*

Identifying the cognitive components that are characteristic for ADHD may improve the understanding of the emotional and social aspects of the disorder (Alloway et al., 2005; Hilton et al., 2017; Huang-Pollock et al., 2009; Kofler et al., 2018, 2017; Moffitt et al., 2011; Thorell, 2007; Tseng & Gau, 2013). For instance, research has shown that the severity of cognitive deficits (e.g., impairment in working memory; deficits in conflict resolution) modulates the frequency of problems in social interactions and overall ADHD symptom-severity (Alloway et al., 2005; Forns et al., 2014; Hilton, 2017; Huang-Pollock et al., 2009; Kofler et al., 2018, 2017; Thorell, 2007; Tseng & Gau, 2013). Associations between cognitive components (derived from cognitive tests) and behavior (observed in other contexts) seem plausible given that cognitive components characterize a participant's general decision process. For example, studies in aging research have found high correlations between drift rates of different tasks (Ratcliff et al., 2006, Ratcliff, Thapar, et al., 2007). They also found associations between drift rates and other measures such as IQ and reading scores (Ratcliff et al., 2008, 2010, 2011; Schmiedek et al., 2007).

### *Reason 3: Different ADHD Endophenotypes May Have Deficits That Affect Their Decision Process at Different Time Points*

Characterizing ADHD endophenotypes by biological markers alone has had only moderate success (Coghill et al., 2005; Killeen, 2019; Nigg, 2005). Computational psychiatry may help to link advances in epidemiology, genetics, and basic neuroscience with

[1] In this review, the term *ADHD endophenotypes* is used as an umbrella term to refer to unspecified subtypes and to account for the fact that a diagnosis of ADHD is frequently accompanied by various co-morbid diagnoses.

[2] Some tasks integrate neurophysiological measures and are often also referred to as neurocognitive tests. However, many tasks, referred to as neurocognitive tests, do not involve any neurophysiological measures. Henceforth, we refer to the term *cognitive tasks* and include those with and without neurophysiological measures.

cognition and behavior. For instance, sequential sampling models not only allow for the study of separate cognitive components, but they also allow for the examination of how these components change as a function of neural activity. One can link model parameters with neurophysiological measures to obtain a meaningful psychological interpretation of the neural activity (Forstmann et al., 2016; Palestro et al., 2018; Ratcliff et al., 2016; Turner et al., 2017). The association of neurophysiological measures with specific cognitive components is, by itself, an interesting domain of study. However, for this article, the important fact is that associations between neural activity and model parameters might allow the study of individual differences and the estimation of symptom severity. We will elaborate more on this in the Discussion section: Suggestions for Integrating Neural Measures.

## Current Limitations in Cognitive Testing for ADHD

The limited understanding of ADHD has increasingly encouraged the assessment of ADHD by administering cognitive tests such as the Continuous Performance Test (CPT; see Moreno-García et al., 2015). The underlying assumption of cognitive testing is that the study of speeded decision-making processes in such clinical settings reveal clinically significant cognitive deficits. To sufficiently account for different ADHD endophenotypes, a combination of multiple cognitive tests is required (Nikolas et al., 2019). However, current review articles are predominantly focused on one test domain (e.g., CPT: Huang-Pollock et al., 2012), or the study of one cognitive concept (e.g., inhibitory control: Nichols & Waschbusch, 2004; Nigg, 2001), or the inclusion of specific groups of participants with ADHD (e.g., children with ADHD: Epstein et al., 2011; adults with ADHD: Nikolas et al., 2019; Woods et al., 2002). To date, findings from studies that evaluated performance differences between participants with and without ADHD, for different types of ADHD groups, and across a wide range of cognitive tests, have not been synthesized. Additionally, studies that used computational model analyses to investigate group differences, as well as individual differences, have not been critically reviewed. There are some meta-analyses with the diffusion decision model (for specific test domains) that we integrated into this review (Huang-Pollock et al., 2012; Mowinckel et al., 2015).

## Objectives of This Article

The objectives of this review are four-fold: First, the review of a range of cognitive tests to identify test procedures (e.g., type of tasks; task specifics; conditions) that are sensitive for measuring ADHD characteristics. Second, the synthesis of sample characteristics (e.g., gender, age, subtypes, comorbid diagnoses) to provide an overview of the heterogeneity of participants with ADHD. Third, the reconciliation of the mixed evidence by incorporating findings from cognitive psychology about the specific effects of different test procedures (e.g., stimulus types, interstimulus intervals). Fourth, the examination of three classes of computational models to summarize new findings and to identify important factors for the proper application of such models. By pursuing the four objectives, this article produces an overview of the field of cognitive testing for ADHD. Moreover, we integrate findings from cognitive psychology into the literature of cognitive testing because cognitive research after 1970 has had relatively little impact on the domain of cognitive testing. We will show (e.g., the section on the test domain: Cognitive Flexibility) that contradictory findings between studies can be reconciled when considering differences in test design, such as with cue-stimulus intervals (CSI). Moreover, we provide recommendations for computational model applications to guide the increasing use of this approach in the field of cognitive testing.

# Method

We first describe the search procedure as well as the inclusion and exclusion criteria for the research reviewed. We then explain how we organized the included studies to synthesis their findings.

## Literature Search

We searched four academic databases for published studies: namely, PsycINFO, PubMed, ProQuest, and EBSCO and we also searched Google Scholar. The search strategy for all five sources used the following keywords "ADHD" AND "cognition," OR "cognitive characteristics," OR "cognitive deficits," OR "cognitive flexibility," OR "conflicting information," OR "continuous performance," OR "comorbidities," OR "computational," OR "distractibility," OR "cognitive tests," OR "task switching," OR "subtypes," OR "slow cognitive tempo." In addition, we examined the reference list of each paper for further studies and screened the google scholar profiles of several researchers in the field.

## Inclusion/Exclusion Criteria

We centered this review on studies that employed cognitive tests and that either examined group differences between participants with and without ADHD or between participants with different ADHD endophenotypes. Studies were included if they provided performance measures of both accuracy values and RTs. We focus on these two measures because these are the conventional metrics for measuring performance in cognitive tasks and these measures serve also as input data for the computational models commonly applied in the field of cognitive testing. However, we also included studies that focused on either accuracy values or RTs if their findings suggested differences between ADHD endophenotypes. We did so because research on ADHD endophenotypes in the domain of cognitive tests is relatively sparse. Moreover, we did not exclude any studies based on perceived methodological weaknesses (e.g., characteristics of the cognitive task, sample size, or diagnostic criteria). However, studies were excluded when their main purpose was the examination of treatment outcomes (e.g., medication, behavioral, or neural interventions). We did not include brain imaging studies, although references to such studies are provided when they are relevant to the discussion. The literature search yielded 50 studies that met the above criteria.

## System of Study Classification

Reviewing a large range of cognitive tests for ADHD hints at six test domains, which seem to identify the cognitive concepts sensitive to ADHD characteristics. Table 1 provides an overview of these domains, with the second column describing the cognitive

**Table 1**
*Six Test Domains to Classify Studies Discussed in This Review*

| Test domain | Cognitive concepts | Common tasks | Reviewed studies |
|---|---|---|---|
| Cognitive flexibility | Coordinated interplay between the activation and the inhibition of multiple control processes. | Task-switch paradigms; Stroop tasks; Navon tasks; Flanker tasks; Antisaccade tasks | 11 |
| Selective attention | Ability to maintain focus on a stimulus in the presence of distractors. | Stroop tasks; Perceptual discrimination tasks; Attentional network tasks; Flanker tasks; Contextual cueing paradigms; Navon tasks; Attentional blink tasks; Antisaccade tasks | 11 |
| Working memory | Cognitive processes that allows an individual to temporarily hold information readily for a prompt usage in a subsequent decision. | *N*-back tasks; Sternberg tasks | 5 |
| Time perception | Judgments about the duration of processes or how much time has passed. | Duration differentiation tasks; Time reproduction tasks | 4 |
| Sustained attention | Ability to maintain attention over an extended period of time. | Continuous performance tasks; Navon tasks | 5 |
| Inhibitory control | Withholding ongoing actions in the presence of new information. | Stop-signal tasks; Stroop tasks; Continuous performance tasks | 14 |



concepts intended to be studied and the third column listing the most commonly used tasks for each test domain.

We grouped the 50 reviewed studies based on their test domain. This approach allowed us to cluster and to discuss research that attempted to examine the same cognitive concepts. However, Table 1 illustrates that some tasks are used to examine multiple test domains (by sometimes changing the details of the test procedures). Moreover, it seems that several tasks likely assess multiple cognitive concepts. It is possible to argue that these test domains are defined mainly (or historically) by the tasks that are used and not by the processes that might be involved in performing the tasks. Therefore, they have not been conceptually organized by the cognitive components that are most sensitive to the detection and study of ADHD.

We emphasize that Table 1 is not an exhaustive list of test domains (or task types) in cognitive testing for ADHD. For instance, research (Castellanos et al., 2005; Douglas, 1999; Goth-Owens et al., 2010; Hervey et al., 2006; Huang-Pollock, Shapiro, et al., 2017; Karalunas et al., 2012; Kuntsi & Stevenson, 2001; Leth-Steensen et al., 2000; Weigard & Huang-Pollock, 2017) suggests slow processing speed to be another prominent characteristic of ADHD. Most studies in this domain utilized RTs as a proxy for processing speed (Forns et al., 2014; Togo et al., 2015). However, research that utilized computational models illustrates that RTs are a product of multiple processes (e.g., Ratcliff & McKoon, 2008; Ratcliff et al., 2012). Therefore, processing speed was not used as a major concept in this review; it is nevertheless implicitly represented in this review because of the focus on research that measured RTs.

## Frequently Used Cognitive Tests

Some reviewed studies employed the same class of cognitive tests. Therefore, Table 2 provides descriptions of the standard format and the general findings for these tasks. A more comprehensive overview and description of these and other cognitive tests can be found in Spreen and Strauss (1998).

## Frequently Applied Computational Models

The following three classes of computational models have been most commonly applied to cognitive tests (see Figure 1): diffusion decision models (DDM; Ratcliff, 1978), absolute accumulator models (AAM; Smith & Vickers, 1988), and ex-Gaussian distribution models (EGDM; Hohle, 1965; Ratcliff, 1979).

Table 3 provides descriptions for the three classes of computational models. Most importantly, the DDM and the AAM both belong to the class of sequential sampling models that were developed in the 1960s and 1970s and that are based on the most dominant theory of how people make speeded. These sequential sampling models are particular appealing because they allow the decomposition of performance (i.e., RTs and accuracy) from laboratory tasks into underlying cognitive components that can be separately studied (see for a review: Forstmann et al., 2016; Ratcliff & Smith, 2004). Moreover, sequential sampling models account for both correct and error RT distributions (and corresponding accuracy rates) and allow researchers to derive parameters that are psychologically interpretable. In contrast, the EGDM does not account for error responses and accuracy rates, only correct responses, and the derived model parameters do not have a straightforward psychological interpretation (Matzke & Wagenmakers, 2009) but rather provide a compact description of RT distributions (Ratcliff, 1979).

## Findings Across Six Test Domains

The six test domains (i.e., Cognitive Flexibility, Selective Attention, Working Memory, Time Perception, Sustained Attention, Inhibitory Control) are discussed in separate subsections below. Each subsection is divided into four parts. After an introduction to the test domain, the second part synthesizes findings from studies that used summary statistics. The third part discusses findings from studies that applied computational models. The fourth part summarizes findings from neurophysiological measures collected during cognitive testing. Tables 4

**Table 2**
*Description of Common Cognitive Tasks*

| Task | Description of task paradigm |
|---|---|
| Continuous Performance Task | The Continuous Performance Task (CPT) is one of the most commonly administered tests. It is designed to assess cognitive concepts such as "inhibitory control," "vigilance," and "sustained attention" (Huang-Pollock et al., 2012; Spreen & Strauss, 1998). Within the framework of cognitive psychology, the CPT belongs to the class of go/no-go tasks (Gomez et al., 2007; Ratcliff et al., 2018). In a go/no-go task, a series of stimuli (e.g., letters, words, nonwords, or symbols) are presented. Usually, one stimulus type represents go trials, while another type represents no-go trials. Participants are asked to press a response key for go trials while refraining from pressing any response key for no-go trials. For clinical use, there are currently three versions of the CPT on the market, which differ in the relative proportion of go/no-go trials and which we will introduce in the following (Edwards et al., 2007). |
| | To assess cognitive concepts such as "vigilance" and "sustained attention," go trials are rare (usually 10%), while no-go trials are frequent (usually 90%). This version of the CPT is often referred to as "Sustained Attention to Response Task" (SART, Robertson et al., 1997); or "Gordon Diagnostic System Vigilance Task" (GDS, Gordon, 1986). Experimental evidence (Huang-Pollock et al., 2006; Sergeant et al., 1999) suggests that participants with ADHD exhibit increased errors to no-go trials, slower mean RTs, and greater variability in RTs as compared with participants without ADHD. We subsequently refer to this class of CPTs as "CPTs." |
| | To assess cognitive concepts such as "inhibitory control" and "impulsivity," go trials are frequent (usually between 75% and 90%), while no-go trials are rare (usually 10%). To this version of the CPT is often referred to as "Conners' Continuous Performance Task" (CCPT, Conners, 1994, 2002). We subsequently refer to this class of CPTs as "CCPTs." Therefore, the main difference between CPTs and CCPTs are the relative proportion of go and no-go trials. Experimental evidence (see for a review: Parsons et al., 2019) suggests that participants with ADHD commit more errors than participants without ADHD. However, results are inconclusive in that some studies found large differences between participants with and without ADHD, while other studies found small or no differences (Corkum & Siegel, 1993; Huang-Pollock et al., 2012; Losier et al., 1996; Nigg, 2005; Sonuga-Barke et al., 2008; Willcutt et al., 2005). Note that the "Test of Variables of Attention" (TOVATM, Greenberg, 1987; Greenberg & Waldmant, 1993) includes a CPT and a CCPT because it has blocks of frequent "go trials" (77.5% go trials vs. 22.5% no-go trials) and blocks of rare "go trials" (22.5% go trials vs. 77.5% no-go trials). |
| Flanker Task | Different versions of the Flanker task (Eriksen & Eriksen, 1974) have been used for clinical assessments (e.g., Fan et al., 2002, 2005; Johnson et al., 2008; Posner & Petersen, 1990). This task is also often also referred to as Attentional Network Task (ANT). Flanker tasks involve neutral, congruent, and incongruent trials. On each trial, a target stimulus (e.g., right—or left—pointed arrow) is presented, accompanied by surrounding stimuli (e.g., arrows) referred to as flankers. For incongruent trials, these flankers are incompatible (e.g., pointing towards the opposite direction of the target arrow), whereas for congruent trials, these flankers are compatible (e.g., pointing towards the same direction as the target arrow). Participants have to respond only to the target stimulus (e.g., direction of the target arrow). On neutral trials, the flankers are unrelated to the target stimulus. Different versions of the task are used to examine different cognitive concepts such as "selective attention" (Ridderinkhof et al., 1999), "inhibitory control" (Forns et al., 2014), and "cognitive flexibility" (Kopp et al., 1994; Rueda et al., 2004). Experimental evidence suggests that participants' performance is slower and more error-prone for incongruent trials as compared with those for congruent and neutral trials (Eriksen & Eriksen, 1974; Heil et al., 2000; Kopp et al., 1996). The study by Jonkman et al. (1999) is representative of several studies. They found that children with ADHD produced more errors than children without ADHD on incongruent trials, yet children with and without ADHD had similar mean RTs. The two groups by Jonkman et al. (1999) were age- and gender-matched, but the majority were boys. Other studies did not find any differences between participants with and without ADHD (Booth et al., 2007; Forns et al., 2014; Huang-Pollock & Nigg, 2003; Johnson et al., 2008; Konrad et al., 2006; Oberlin et al., 2005). |
| Navon Task | The Navon task (Navon, 1977) serves to assess the degree to which a participant focuses on processing global versus local features of a stimulus. In the standard version of the task, participants are presented with a large letter (global) comprised of small letters (local). The small letters and the large letter are either the same (congruent condition) or different (incongruent condition). Participants are instructed to name either the large letter (i.e., global feature) or the small letters (i.e., local feature). There exist multiple versions of this task, which are used to investigate different cognitive concepts such as "selective attention" (Song & Hakoda, 2012; Volberg & Hübner, 2004) and "sustained attention" (Helton, 2009). Studies have shown that specific details of the task lead to different results (Gerlach & Poirel, 2018; Happé & Frith, 2006; Kimchi, 1992; Navon, 2003; Yovel et al., 2001). However, the following three effects are generally obtained: First, faster responses are made to global versus local features (a global precedence effect); second, slower responses are made for incongruent versus congruent trials (an interference effect); third, slower responses are made for incongruent trials when the participant is cued to process locally, than when cued to process globally (an inter-level interference effect). |
| | Evidence is mixed on whether the Navon task is sensitive to the detection of characteristics specific to ADHD. Some studies suggest that participants with ADHD show a greater interference effect compared with participants without ADHD (e.g., Song & Hakoda, 2012). Other studies did not find performance differences between participants with and without ADHD (e.g., Kalanthroff et al., 2013). The fact that results are mixed suggests that the detection of clinical characteristics in this task depends substantially on the task specifics. |

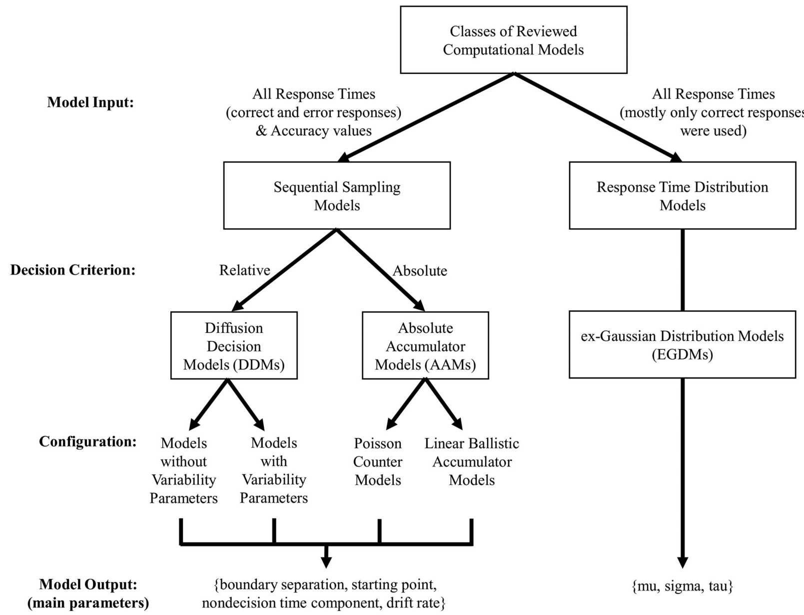
(*table continues*)

**Table 2** (*continued*)

| Task | Description of task paradigm |
|---|---|
| *N*-Back Task | In the *N*-back task (Kirchner, 1958), participants are presented with a sequence of stimuli (e.g., letters, symbols, numbers, words, pictures). For each stimulus, they need to indicate whether it was presented on the Nth trial before the current stimulus. For instance, in a 1-back task, participants decide whether the current stimulus is identical to the one previously presented (1-back). In most studies, participants are asked to press a key if the current stimulus is the same as the one presented *N* trials before. For nontarget stimuli, participants have to withhold keypresses. However, in some studies, participants are required to respond to each stimulus by pressing different keys for target and nontarget stimuli (e.g., Cohen et al., 1997; Harvey et al., 2005; Miller et al., 2009; Perlstein et al., 2003). Multiple versions of the *N*-back task are used to examine cognitive concepts such as "working memory" (Jaeggi et al., 2010; Soveri et al., 2017; Szmalec et al., 2011) and "inhibitory control." (Irlbacher et al., 2014; Szmalec et al., 2011). The test becomes more difficult (i.e., slower RTs or lower accuracy, or both) the longer a stimulus needs to be maintained in WM, for example, the longer the lag (larger N) or the longer the interstimulus interval (ISI), (e.g., Cohen et al., 1997; Harvey et al., 2005; Miller et al., 2009; Perlstein et al., 2003;). We will later review results suggesting that participants with different ADHD subtypes elicit deficits in distinct cognitive components (Carr et al., 2010; our section on cognitive flexibility). |
| Time Discrimination Task | In time reproduction tasks, participants have to guess time intervals of stimuli a priori presented for different amounts of times. In time differentiation tasks, participants are shown multiple stimuli that differ in their presentation duration. Participants are asked to select the stimuli that were presented the longest and/or shortest. Many lines of research suggest a disturbed sense of time in participants with ADHD (Barkley et al., 1997; McInerney & Kerns, 2003; Smith et al., 2008). |
| Sternberg Task | The Sternberg task is designed to measure participants' working memory (WM; Sternberg, 1967). The Sternberg task can be divided into three phases as follows: in the encoding phase, participants are asked to memorize a list of items (e.g., numbers, words, dots appearing at different locations on the screen). In the subsequent maintaining phase, participants are commonly asked to perform another, unrelated distractor task, to prevent active rehearsal of the memorized items. In the final retrieving phase, participants are asked whether particular test item have or have not been presented before. Sternberg (1967) found that RTs increased with the size of items that had to be memorized during the encoding phase.<br>Burgeoning research proposes that deficits in WM are a robust characteristic for ADHD (Buzy et al., 2009; Lenartowicz et al., 2014; Weigard & Huang-Pollock, 2017; Willcutt et al., 2005). However, the underlying cognitive components that lead to WM deficits remain a topic of debate. Some studies suggest that WM deficits are a consequence of limited prefrontal capacities (e.g., Friedman-Hill et al., 2010; Lavie & De Fockert, 2003). Other studies suggest that WM deficits are attributable to impairments in controlling attention (e.g., Friedman-Hill et al., 2010; Huang-Pollock et al., 2006); or to biased processing of information (e.g., Lenartowicz et al., 2014). |
| Stop-Signal Task | The Stop-Signal task is designed to measure inhibitory control processes (Crosbie et al., 2013; Logan et al., 1984; Logan et al., 2014; Nigg, 1999; Willcutt et al., 2005), and is conceptualized as a go/no-go task. As in the CPT, participants need to respond quickly to go trials. In contrast to the CPT, some of the go trials are followed by a signal (e.g., typically an auditory tone), which requires participants to stop their ongoing response. It is hypothesized that the mean stop-signal reaction time (SSRT), which represents the difference between go stimulus onset and stop-signal onset, indexes the efficiency of cognitive control processes. Research has found that children with ADHD exhibit significantly slower RTs compared with children without ADHD for go trials in blocks with intermittent stop signals compared with controls (with medium effect sizes, see Alderson et al., 2007; Lipszyc & Schachar, 2010; Martel et al., 2007; Nigg, 1999; Willcutt et al., 2005). However, current research questions whether the SSRT indeed indexes efficiency of cognitive control processes and whether cognitive control processes are indeed the characterizing feature of ADHD (Nikolas et al., 2019; Weigard et al., 2019). |
| Stroop Task | In the Stroop task (Stroop, 1935), participants are presented with words of colors and are required to either read the color word or to name the color of the word. The task is composed of incongruent and congruent trials. On congruent trials, the ink color of the word matches the color word. On incongruent trials, the ink color is dissimilar to the color word. The Stroop task measures cognitive concepts such as "cognitive flexibility" (Spreen & Strauss, 1998) and "selective attention" (Spreen & Strauss, 1998). Experimental evidence (Spreen & Strauss, 1998; Stroop, 1935) consistently showed that participants' performance is slower and more error-prone for incongruent trials as compared with congruent trials. Some reviews suggest that children with ADHD show poorer performance than children without ADHD for incongruent trials. They conclude that one characteristic of ADHD is a deficit in the resolution of interference (Barkley, 1997b; Pennington & Ozonoff, 1996). |
| Wisconsin Card Sorting Task | The Wisconsin Card Sorting Task (WCST) is a task-switch paradigm frequently used to study cognitive characteristics such as "cognitive flexibility" and "efficiency of executive control processes" in participants with ADHD (Goldstein & Green, 1995; Romine et al., 2004). In the standard version of this test, participants are asked to sort cards based on their color, shape, or number. The participant has to learn the rule (i.e., which card feature to sort the card: color, shape, or number) based on feedback messages (i.e., correct/incorrect). The rule usually changes every eleventh trial and so the WCST measures not only cognitive flexibility but also a participant's ability to learn the rule. Accuracy values index the performance on the WCST. Conducting a meta-analysis, Romine et al. (2004) found that participants with ADHD had poorer performance (i.e., a higher error rate) on the WCST as compared with participants without ADHD. The test can be difficult to administer, because it requires participants to tolerate frustration as newly learned rules must be updated unexpectedly and multiple times during the test (Robinson et al., 1991; Smith-Seemiller et al., 1997). |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time.

**Figure 1**
*Overview of the Computational Models Included in This Review*




to 9 list the main findings for each study. Table A1 in the Appendix includes more information about study-specific tasks. Tables A2–A7 in the Appendix provide sample characteristics and summary statistics and/or model parameter values to assess effect sizes for each study.

## Cognitive Flexibility

Cognitive flexibility is commonly studied using paradigms in which participants have to switch back and forth between either different features of the same stimulus (e.g., global vs. local features as in Navon tasks; Table 2) or between different tasks (e.g., task-switch paradigms; see for review: Gajewski et al., 2018). Research from cognitive psychology suggests that switching between tasks and/or stimulus features involves a coordinated interplay between activation and inhibition of various executive control processes[3] (Cepeda et al., 2001; Hasher et al., 2007, 1999; White & Shah, 2006). Specifically, when switching from task (or stimulus feature) *A* to task (or stimulus feature) *B*, the cognitive processes which are configured to the specifics of *A*, need to be inhibited. Next, the cognitive processes need to be reconfigured to the specific requirements of *B* (e.g., Cepeda et al., 2000; Rubinstein et al., 2001). Paradigms generally involve *pure blocks* (i.e., pure trials) in which participants need to focus on one task (or stimulus feature) and *mixed blocks* (i.e., no-switch and switch trials) in which participants need to switch between tasks (or stimulus feature) on some trials. Performance is typically slower and more error-prone when participants switch between multiple tasks (or stimulus features) than when they focus on the same task (or stimulus feature; e.g., Rogers & Monsell, 1995; Rubinstein et al., 2001; Schmitz & Voss, 2012). *Global switch costs* refer to the performance difference between pure and no-switch trials, whereas *local switch costs* refer to the performance difference between no-switch and switch trials.

### Findings From Summary Statistics

In Hung et al.'s (2016) study, boys with and without ADHD performed a task-switch paradigm that involved two numeracy judgment tasks. They found larger global switch costs (but similar local switch costs) for boys with ADHD as compared with those without ADHD (see Table 4). Similar results were also obtained in other research that involved adults (McLean et al., 2004; White & Shah, 2006). This contrasts with most research in cognitive psychology, which also found local switch costs in terms of both accuracy and mean RTs (Ging-Jehli & Ratcliff, 2020; Rogers & Monsell, 1995; Rubinstein et al., 2001; Schmitz & Voss, 2012). The absence of local switch costs in Hung et al.'s study could indicate that task-switching in their paradigm was undemanding because the two tasks used in their task-switch paradigm were similar (Table A1). Research in cognitive psychology suggests large local switch costs particularly in task-switch paradigms that involve unrelated tasks. Hence, task-switch paradigms composed of tasks that tap into different cognitive domains may be more sensitive to study clinical characteristics in terms of switch costs.

Whereas Hung et al. (2016) examined ADHD-related differences in global and local switch costs, Cepeda et al. (2000) focused only on local switch costs but as a function of response congruency. In their

[3] The concept of *executive control processes* (also referred to as *executive functioning*) is often not well defined. There exist diverse descriptions (Morgan & Lilienfeld, 2000; Pennington, 1997). In this article, we follow a neurocognitive framework to define this concept. Specifically, *executive control processes* (or *executive functioning*) refers to context-specific regulations of responses to perform a neurocognitive test (Pennington & Ozonoff, 1996).

**Table 3**
*Description of Computational Models Covered in This Study*

| Model | Description of model |
|---|---|
| Absolute accumulator models (AAMs) | Absolute accumulator models (AAMs), alternatives to DDMs (explained below), belong to the class of sequential sampling models (for comparisons among the models see Forstmann et al., 2016; Ratcliff & Smith, 2004). The underlying assumption of sequential sampling models is that evidence for one (or more) response alternatives are accumulated over time until a particular decision criterion (i.e., threshold of evidence) is reached (Forstmann et al., 2016; Van Zandt et al., 2000).<br>AAMs introduce a separate decision process (i.e., accumulator) for each response alternative. Hence, it is assumed that evidence is accumulated for each possible response independently and separately. The rate of evidence accumulation for each counter is referred to as drift rate. In contrast, the DDM introduces one decision process for all response alternative so that the rate of evidence accumulation (i.e., drift rate) represents the net evidence for a particular response. There are multiple versions of AAMs that vary in their underlying assumption about whether evidence accumulation processes are noisy and/or vary across trials (e.g., Racing Diffusion Model; Van Zandt et al., 2000; Linear Ballistic Accumulator Model; Brown and Heathcote, 2008; accumulator and counter models, Ratcliff & Smith, 2004; Leaky competing accumulator model, Usher & McClelland, 2001).<br>AAMs typically decompose the task performance into components that closely resemble the DDM's main model parameters (i.e., drift rate, nondecision time component, boundary separation, and starting point; see for a review: Donkin et al., 2011; Donkin & Brown, 2018). |
| Diffusion decision models (DDMs) | The diffusion decision model (DDM, Ratcliff, 1978) utilizes accuracy and RT data to decompose the task performance into separable cognitive components, namely: the quality of information driving the decision process (drift rate, v), the amount of evidence used to reach a decision (boundary separation, a), the duration of perceptual encoding and response execution (nondecision time component, Ter), and a priori expectations (starting point, z) (Forstmann et al., 2016; Ratcliff, 1978, 1985, 1987; Ratcliff & McKoon, 2008). The model is also appealing because the assumption about decision processes closely resembles our understanding of brain functioning and dynamics. For instance, multiple studies provide neuronal evidence for the existence and dynamics of the cognitive components suggested above. Specifically, they demonstrate that distinct brain areas are active during different stages of the decision process (Cohen & Kohn, 2011; Gold & Shadlen, 2001; Gold & Shadlen, 2007; Hanes & Schall, 1996; Philiastides et al., 2006; Ratcliff et al., 2003; Ratcliff, Hasegawa, et al., 2007; Wong et al., 2007).<br>The DDM has been used in a range of research fields. Its parameters have validated cognitive interpretations (Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998; Ratcliff et al., 2016; Ratcliff et al., 1999; Voss et al., 2004). Moreover, the diffusion model has successfully accounted for the cognitive task data from a wide range of clinical participant populations such as ADHD, autism, depression, anxiety, aphasia, and dyslexia, among others (Caulfield & Myers, 2018; Moustafa et al., 2015; Pe et al., 2013; Perugini et al., 2016; Pirrone et al., 2020; Ratcliff et al., 2004; White et al., 2010a, 2010b; Zeguers et al., 2011).<br>The model incorporates more information than most others as it simultaneously accounts for RT distributions of correct and error responses as well as for accuracy across all the conditions of an experiment. This allows the study of components of processing found in rapid decision making. For instance, long RTs can be the result of emphasizing accuracy over speed (i.e., large a), or it can be the result of slowed peripheral processes unrelated to the decision process itself (i.e., a longer Ter). Understanding how parameters change across conditions allows an assessment of a participant's ability in adjusting multiple cognitive components. This may help to account for the heterogeneity observed in ADHD because it allows to locate the various cognitive processes that can be dysfunctional (or atypical) for ADHD. Moreover, model parameters for multiple cognitive tasks can be used to examine both group differences and intra-individual differences. Eventually, the model may link cognitive concepts to neuronal measures (Forstmann et al., 2016; Palestro et al., 2018; Ratcliff, Sederberg, et al., 2016; Ratcliff, Smith, et al., 2016) which has the advantage of potentially assigning psychological interpretations to the observed neural activity. |
| Ex-Gaussian distribution models (EGDMs) | Descriptive distributions such as the ex-Gaussian are used to derive estimates that characterize the shape of the entire RT distribution. The ex-Gaussian distribution is produced from the convolution of a Gaussian distribution and an exponential distribution, that is, the sum of an exponential random variable and a Gaussian random variable (Hohle, 1965; Luce, 1986; Ratcliff & Murdock, 1976). This produces a positively skewed unimodal shape that mirrors most RT distributions found in experimental paradigms (Heathcote et al., 1991; Hockley, 1982, 1984; Hohle, 1965; Ratcliff, 1978, 1979; Ratcliff & Murdock, 1976). The ex-Gaussian distribution is characterized by three parameters, namely mu ($\mu$) and sigma ($\sigma$), which index the mean and standard deviation of the Gaussian component; and tau ($\tau$), which indexes the mean of the exponential component. Informally, changes in mu represent changes in the peak of the distribution, sigma the rise in the leading edge, and tau the spread in the tail of the distribution.<br>We will show that most studies found larger tau values for participants with ADHD compared with those of participants without ADHD. It is important to keep in mind that the ex-Gaussian distribution is a purely descriptive model. This means that the model parameters do not provide well-established psychological interpretations. However, some researchers suggested that larger tau values would indicate lapses of attention (Hwang-Gu et al., 2019; McVay & Kane, 2012; Metin et al., 2016; Tye et al., 2016). They concluded that this intra-individual response variability could be utilized as a diagnostic criterion (Henríquez-Henríquez et al., 2015; Shahar et al., 2016; Tarantino et al., 2013). However, whether a larger tau is indeed a result of lapses of attention has not been verified to date. In fact, studies showed that larger tau values can have different cognitive sources (for reviews see: Gomez et al., 2007; Huang-Pollock, Shapiro, et al., 2017; Matzke & Wagenmakers, 2009; Wiecki et al., 2015). |

**Table 3** (*continued*)

| Model | Description of model |
|---|---|
| | Moreover, studies have repeatedly shown that the psychological interpretation of the parameters from the ex-Gaussian distribution do not uniquely map to specific cognitive components from other, more detailed computational models (Matzke & Wagenmakers, 2009; Ratcliff, 1978). Current applications have mostly used the RT distributions of either correct or error responses, but rarely both. The DDM (Ratcliff, 1978) examined above, is a model that simultaneously accounts for RT distributions of correct and error responses and that overcomes these shortcomings. |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time.



study, children with and without ADHD performed a task-switch paradigm that involved two number discrimination tasks (each task consisted of congruent and incongruent trials). Cepeda et al.'s findings (see Table 4) suggest that task-switch paradigms composed of related tasks can be sensitive to clinical characteristics (i.e., produce significant group differences), if "congruency" of responses to the tasks is manipulated.

Based on the findings discussed so far, the detection of clinical characteristics in task-switch paradigms seems to depend highly on the specifics of the paradigms (i.e., types of tasks, congruency of stimuli). This view is further supported by Oades and Christiansen (2008), who used the same paradigm as Cepeda et al. (2000), but with some modifications (i.e., a longer CSI and with task switches occurring randomly rather than predictably). Whereas Cepeda et al. found group-specific differences in local switch costs in terms of only mean RTs, Oades and Christiansen found group-specific differences in local switch costs in terms of only accuracy. These different results regarding the types of local switch costs can be explained by findings from cognitive psychology (Rogers & Monsell, 1995; Rubinstein et al., 2001; Schmitz & Voss, 2012; Vandierendonck et al., 2010). Random task switching usually results in larger switch costs compared with those from predictable task switching (Schmitz & Voss, 2012). However, increases in CSI usually results in much smaller switch costs. Therefore, increasing CSI in Oades and Christiansen's study may have given participants enough time for switching between tasks without time costs, even though task-switches occurred randomly. These findings could further suggest that ADHD is characterized by deficient control processes associated with task switching and allowing for enough time to prepare switches between tasks may compensate for these deficits.

Multiple explanations exist for ADHD-specific deficits in task switching. For instance, Luna-Rodriguez et al. (2018) hypothesized that ADHD-specific increases in local switch costs[4] would be attributable to deficits in switching attention to different perceptual attributes of a stimulus. In their study, adults with and without ADHD performed a task-switch paradigm (composed of a letter and a number discrimination task). Accuracy values were high for all adults and all conditions (Table A2), which suggests that the task-switch paradigm was undemanding and probably not sensitive enough to produce group-specific differences. Song and Hakoda (2012) refined Luna-Rodriguez et al.'s hypothesis proposing that the deficits in switching attention to different perceptual attributes of a stimulus is a characteristic particularly of ADHD-I. In a modified Navon task (involving large letters [global condition] composed of smaller letters [local condition]; Table A1), children with ADHD-I experienced greater interference from the local stimulus features when asked to process the global stimulus features. Other studies (Chun & Potter, 1995; Duncan et al., 1994; Hommel et al., 2006) support the findings of Song and Hakoda and Luna-Rodriguez et al. Synthesizing the findings across studies discussed thus far suggests that ADHD-specific local switch costs arise from deficits in switching attention to different stimulus features and that these deficits are a characteristic of ADHD-I.

Given that the children in Song and Hakoda's (2012) study were only required to switch between stimulus features but not between tasks, it may seem surprising that Luna-Rodriguez et al. (2018) did not find any group differences in accuracy (see Table 4). One difference between the two studies is that the participants in Luna-Rodriguez et al.'s study were adults, whereas participants in Song and Hakoda's study were children (Table A2). There is also an important methodological difference between the two studies: in Luna-Rodriguez et al.'s study, trials started with a blank screen, followed by the cue and then the stimulus. In contrast, Song and Hakoda administered the task with paper and pencil (Table A1). Hence, it can be argued that in Luna-Rodriguez et al.'s study, the sequential presentation of cues and stimuli, one at a time, helped particularly participants with ADHD (maybe by structuring the task for them). This conclusion is consistent with the findings of Oades and Christiansen (2008) and Cepeda et al. (2000), previously discussed, and suggests that deficits in ADHD are more prominent when the time to restructure thoughts is short rather than long.

The results from studies initially discussed suggested subtype-specific differences in switch costs. Baytunca et al. (2018) examined this further by subgrouping children with ADHD into either ADHD-only or ADHD + SCT based on parent- and teacher-rated scores on the slow cognitive tempo scale (McBurnett et al., 2001). Children then performed a task-switch paradigm (classifying geometric figures either based on their color or shape). Instead of reporting switch costs in terms of mean RTs and accuracy, Baytunca et al. reported cognitive flexibility scores which were derived from several tasks.[5] Their results (see Table 4) support the view that impairments in cognitive flexibil-

[4] It was not specified whether switch costs were measured in terms of RTs or accuracy.

[5] Baytunca et al. (2018) administered a battery of cognitive tests including a Flanker task (i.e., SAT) and the Stroop task (Table 2; see also Gualtieri & Johnson, 2006). The Cognitive Flexibility scores discussed in this section were calculated by subtracting the number of error responses (i.e., total errors from the Flanker task plus the commission errors from the Stroop task) from the number of correct responses from the Flanker (higher scores are better).

**Table 4**
*Summary of Main Findings for Test Domain: Cognitive Flexibility*

| Authors | Tasks | Main behavioral findings |
|---|---|---|
| Hung et al. (2016) | Task-switch paradigm. For details, see Table A1. | Boys with ADHD had three times larger global switch costs in terms of accuracy (but not in terms of mean RTs) than boys without ADHD. Neither boys with ADHD nor boys without ADHD showed any local switch costs (neither in terms of accuracy nor mean RTs). |
| Cepeda et al. (2000) | Task-switch paradigm with congruent and incongruent trials. For details, see Table A1. | For incongruent trials, children with ADHD had three times larger local switch costs in terms of mean RTs (but not in terms of accuracy) than children without ADHD. For congruent trials, children with and without ADHD had similar local switch costs. |
| Oades and Christiansen (2008) | Task-switch paradigm. For details, see Table A1. | Children with ADHD (as well as their siblings) had two times larger local switch costs in terms of accuracy (but not in terms of mean RTs) than children without ADHD. |
| Luna-Rodriguez et al. (2018) | Task-switch paradigm with large letters/ numbers (global features) composed of smaller letters/ numbers (local features). For first condition: adults were instructed to switch between two tasks, but to keep their attention to either the global or local stimulus feature. For second condition: adults were instructed to switch between two tasks, and to additionally switch between processing the global versus local stimulus features. For details, see Table A1. | Accuracy values were high for all adults and all conditions ($\geq$ 90.0%). For the first condition, adults with and without ADHD had similar mean RTs. For the second condition, adults with ADHD had significantly slower mean RTs than the adults without ADHD. |
| Song and Hakoda (2012) | Modified Navon task with large letters (global condition) composed of smaller letters (local condition). For details, see Table A1. | For the local condition, children with ADHD-I were as accurate as children without ADHD. For the global condition, children with ADHD-I were significantly less accurate than children without ADHD. |
| Baytunca et al. (2018) | Task-switch paradigm. For details, see Table 2. Wisconsin Card Sorting Task. | The non-ADHD group showed a significantly higher cognitive flexibility score than the ADHD-only group and the ADHD + SCT group. Moreover, the ADHD + SCT group had significantly lower scores than the ADHD-only group. |
| Carr et al. (2010) | Attentional blink task with single and dual conditions. For the single condition: children had to confirm/reject the presence of a probe letter at the end of a letter stream. For the dual condition: children had to confirm/reject the presence of a probe letter and a target letter at the end of a letter stream. For details, see Table A1. | The three groups did not differ in accuracy of probe detection in the single condition. For the dual condition, children with ADD detected significantly more probe letters than children with ADHD-C or without ADHD. |
| Carr et al. (2010) | Antisaccade task with saccade and antisaccade conditions. For the saccade condition: children had to move their eyes towards the position of target boxes. For the antisaccade conditions: children had to move their eyes towards the opposite position of target boxes. For details, see Table A1. | For both conditions, the ADHD-C group had significantly higher error rates than the non-ADHD group (the ADD group had error rates in between those of the ADHD-C and the non-ADHD group). For the antisaccade condition only, both ADHD groups had slower mean RTs than the non-ADHD group. Summary statistics of mean RTs or accuracy values were unavailable. Values of mean RTs and accuracy were estimated from their figures. Based on the figures, the group differences in mean RTs and accuracy values seem small. |
| O'Driscoll et al. (2005) | Antisaccade task (same task as administered by Carr et al., 2010). | Boys with ADHD-C had a significantly larger difference in error rates between the antisaccade condition and the saccade condition than those of boys with ADHD-I and without ADHD. The boys with ADHD-I did not significantly differ from the boys without ADHD. |
| Metin et al. (2013) | Modified antisaccade task. For details, see Table A1. | For the saccade and antisaccade conditions, children with ADHD-C had significantly lower drift rates and shorter nondecision time components than children without ADHD. |
| Salum et al. (2014) | Antisaccade task (same task as administered by Metin et al., 2013). | Children with minimal, moderate, and clinical inattention scores had lower drift rates than asymptomatic children. Moreover, children with clinical symptom scores had shorter nondecision time components than children of all the other groups. |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time; SCT = sluggish cognitive tempo.

**Table 5**
*Summary of Main Findings for Test Domain: Selective Attention*

| Authors | Tasks | Main behavioral findings |
|---|---|---|
| Friedman-Hill et al. (2010) | Picture discrimination task with two levels of discrimination difficulty and three levels of distractor saliency. For details, see Table A1. | For the high-difficulty condition (averaging performance across levels of distractor saliency), children with ADHD had a significantly lower error rate and significantly slower mean RTs than children without ADHD. For the low-difficulty condition, children with ADHD were more distractible (as indexed by significantly higher error rates and significantly slower mean RTs) than children without ADHD. |
| Schneidt et al. (2018) | Perceptual orientation task. For details, see Table A1. | Adults with ADHD had slower mean RTs (but similar accuracy levels) than adults without ADHD. |
| Mulder et al. (2010) | Random-dots motion paradigm with accuracy- and speed-emphasized conditions. For details, see Table A1. | For the accuracy- relative to the speed-emphasized condition, children with ADHD experienced significantly smaller increases in boundary separation than children without ADHD. Additionally, more severe hyperactivity symptoms were associated with smaller increases in boundary separation. Interestingly, children with ADHD had slightly larger boundary separation than children without ADHD for the speed-emphasized condition. Moreover, children with and without ADHD had similar nondecision time components and drift rates for the two conditions. |
| Johnson et al. (2008) | Flanker task. For details, see Table 2. | Children with ADHD made significantly more errors and had significantly slower mean RTs than children without ADHD. |
| Epstein et al. (2011) | Flanker task. For details, see Table 2. | Children with ADHD-C and ADHD-I had (nonsignificant) slower mean RTs than children without ADHD. However, the difference in mean RTs between ADHD-C and ADHD-I seemed large (i.e., 108ms), which suggests that the group difference did not reach statistical significance because there was high variability among children with ADHD. Another explanation could be a low sample size. However, Table A3 shows that the sample included 104 children, so this seems unlikely. Moreover, children with ADHD-C were significantly less accurate than children without ADHD. Accuracy of children with ADHD-I was between those of children with ADHD-C and without ADHD and did not statistical significantly differ from either group. |
| Tegelbeckers et al. (2016) | Flanker task with additional distractors (irrelevant sounds presented at the beginning of some trials). For details, see Table 2. | When sounds were randomly rather than predictably presented, children (with and without ADHD) had increased accuracy, decreased mean RTs, and decreased RT variability. Note that a decrease in mean RTs is usually associated with a decrease in RT variability. |
| Gohil et al. (2017) | Modified flanker task with correct/ incorrect arrows (i.e., primes) subliminally presented between cues and stimuli. For details, see Table A1. | Children with ADHD showed a larger drop in accuracy between conditions with correct relative to incorrect primes but similar mean RTs across all conditions than children without ADHD. Hence, children with ADHD were more strongly affected by subliminal distractors than children without ADHD. |
| Banich et al. (2009) | Stroop task. For details, see Table 2. | Young adults with ADHD showed significantly less interference (i.e., increase in mean RTs from neutral to incongruent trials) than young adults without ADHD. |
| Hasler et al. (2016) | Flanker task. For details, see Table 2. | The ADHD and non-ADHD groups neither differed significantly in mean RTs nor in accuracy; however, accuracy was at ceiling for both groups and the group difference in mean RTs (i.e., 100ms) seemed large (Table A3). Table A3 suggests that this large but insignificant group difference in mean RTs was attributable to the high variability among participants or to the small sample size. |
| Merkt et al. (2013) | Modified flanker task. For details, see Table A1. | Female students with ADHD had slower mean RTs, but fewer errors, than those without ADHD. Moreover, female students with ADHD had lower drift rates, larger boundary separation, and longer nondecision time components compared with those without ADHD. |
| Weigard and Huang-Pollock (2014) | Flanker-like search paradigm with target letters either repeatedly presented in the same locations (RC trials) or in random, new locations (NC trials). For details, see Table A1. | For RC and NC trials, children with ADHD had significantly lower drift rates and lower boundary separation than children without ADHD. |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time.

**Table 6**
*Summary of Main Findings for Test Domain: Working Memory*

| Authors | Tasks | Main behavioral findings |
|---|---|---|
| Epstein et al. (2011) | 1-back task. For details, see Table 2. | Children with ADHD-C and ADHD-I had significantly lower accuracy rates (but similar mean RTs) than children without ADHD. |
| Stroux et al. (2016) | 1- and 2-back task. For details, see Table 2. | In the 1-back task, adults with ADHD were (nonsignificantly) less accurate than adults without ADHD. There were no statistics on RTs. In the 2-back task though, adults with ADHD were significantly less accurate than adults without ADHD. |
| Kawabe et al. (2018) | 1-back task. For details, see Table 2. | Boys with ADHD and those with ADHD and ASD had similar mean RTs and accuracy as boys without ADHD and/or ASD. |
| Lenartowicz et al. (2014) | Sternberg task. For details, see Table A1. | Children with ADHD were slower, less accurate, and exhibited a higher RT variability than children without ADHD. |
| Weigard and Huang-Pollock (2017) | Modified sternberg task and an additional Numerosity task as a distractor task. For details, see Table A1. | In the modified sternberg task, children with ADHD were significantly less accurate than children without ADHD. A DDM analysis applied to the performance from the Numerosity task showed that children with ADHD had significantly lower drift rates and shorter nondecision time components than children without ADHD. |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time; DDM = diffusion decision models; ASD = autism spectrum disorder.

ity are what characterize ADHD and that ADHD comorbid SCT show pronounced impairments. Considering that clinical research found positive associations between SCT and ADHD-I (e.g., Barkley, 2013; Becker & Willcutt, 2019; Carlson & Mann, 2002; McBurnett et al., 2001) further suggests that ADHD-I is not only characterized by greater interference of a stimulus' local features (as previously shown by Song & Hakoda, 2012), but also by an inflexibility to switch between different features of a stimulus (as shown by Baytunca et al.).

The findings discussed so far provide few insights into the differentiating characteristics between ADHD subgroups. Carr et al. (2010) showed in two experiments that differences in early-stage and late-stage attentional filtering processes are what differentiated ADHD-C from ADHD-I. Children with ADHD were subgrouped into either ADHD-C, ADHD-I, or ADD (Table A2). In the first experiment, children with and without ADHD performed an Attentional blink task (Table A1) used to study early-stage attentional filtering processes.[6] Table 4 shows that children with ADD exhibited sensitive early-stage attentional filtering processes (i.e., attentional gating of information at an early-stage; for details see Adams et al., 2008). Considering the findings previously discussed (e.g., Luna-Rodriguez et al., 2018; Song & Hakoda, 2012), Carr et al.'s results refines the current view by suggesting that ADHD-I is characterized by greater stimulus interference due to sensitive early-stage control processes involved in gating attention to specific stimulus features.

In Carr et al.'s (2010) second experiment, children with and without ADHD performed an Antisaccade task (Table A1) used to study late-stage attentional filtering processes. Children with ADHD-C exhibited deficient late-stage attentional filtering processes (see Table 4). This conclusion is supported by the findings of O'Driscoll et al. (2005), who administered the same task to three groups of boys (ADHD-C, ADHD-I, non-ADHD). Note that the error rates in O'Driscoll et al.'s study seemed much larger than the error rates found in Carr et al.'s study (Table A2). Synthesizing the different findings discussed so far suggests that a high severity in inattention but not in hyperactivity/impulsivity (e.g., ADHD-I, ADD) is manifested in deficient early-stage information filtering. Additional high severity in hyperactivity/impulsivity (e.g., ADHD-C) is manifested in deficient late-stage control processes.

### Findings From Computational Model Applications

Metin et al. (2013) administered the same Antisaccade task as Carr et al. (2010) to children with ADHD-C and without ADHD and compared their performance with a DDM analysis. Their results (see Table 4) support the view that ADHD-C is characterized by deficits in late-stage control processes involved in integrating presented information (indexed by drift rates) but intact early-stage control processes involved in perceptual encoding (indexed by nondecision time components).[7]

Salum et al. (2014) used the same paradigm as Metin et al. (2013) and found similar findings. An interesting aspect of Salum et al.'s study is their group categorization of children based on their symptom severity of hyperactivity and inattention (Table A2). This grouping allowed Salum et al. to study whether the magnitude of differences in the DDM parameters would linearly increase with symptom severity. Table 4 illustrates that Salum et al. found significant differences in DDM parameters not only between the asymptomatic non-ADHD group and the clinical ADHD group. Notably, the more severe the ADHD symptoms, the larger the estimated differences in model parameters. The paradigm used by Salum et al. and Metin et al. comprised a low number of trials (i.e., 25 incongruent trials, 75 congruent trials) which makes it difficult to estimate model parame-

[6] The efficacy of early-stage attentional filtering processes was estimated from the accuracy of probe detection in the single and dual condition. Such an analysis is motivated by research (Chun & Potter, 1995; Duncan et al., 1994; Hommel et al., 2006) which showed that the detection of the probe letter is usually high when the probe letter follows immediately (i.e., 90 ms to 200 ms) after the target letter. In contrast, the detection of the probe letter is usually low when the probe letter follows 200 ms to 500 ms after the target letter (referred to as *attentional blink window*). This is because in this window the target letter is processed which takes away resources needed for the detection of the probe letter.

[7] Ging-Jehli and Ratcliff (2020) provide evidence and explanation for the mapping of control processes to diffusion model parameters in the context of a task-switch paradigm. See also the Summary of this test domain in the Discussion section.

**Table 7**
*Summary of Main Findings for Test Domain: Time Perception*

| Authors | Tasks | Main behavioral findings |
|---|---|---|
| Valko et al. (2010) | Time reproduction task. For details, see Table A1. | Children and adults with ADHD were less accurate in reproducing target time intervals than children and adults without ADHD. |
| Valko et al. (2010) | Time differentiation task. For details, see Table A1. | Children with ADHD, compared with those without ADHD, were significantly less accurate (but had similar mean RTs) in selecting the light bulb that lasted longer. In contrast, adults with ADHD, compared with those without ADHD, were similarly accurate (but had significantly slower mean RTs). |
| Marx et al. (2017) | Variety of perceptual timing tasks. For details, see Table 2 and Table A5. | Boys with ADHD were less accurate in estimating time intervals in a range of perceptual timing tasks as compared with boys without ADHD. |
| Shapiro and Huang-Pollock (2019) | Time differentiation task. For details, see Table 2. | Children with ADHD had lower drift rates and longer nondecision time components than children without ADHD. |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time.

ters with any degree of accuracy. Hence, their results need to be interpreted with caution.

### Findings From Neurophysiological Measures

Hung et al. (2016), whose behavioral results were discussed earlier, used EEG to collect event-related potentials (EEG-ERPs) during a task-switch paradigm. The ADHD group had smaller amplitudes and longer latencies in the P3 component than the non-ADHD group (for pure and mixed blocks). Hung et al. did not find any association between switch costs and P3 component (neither in amplitude nor in latency). Other studies support Hung et al.'s findings and suggest further that ADHD-specific deficits in cognitive flexibility arise from insufficient frontal and parietal lobe activation when switching between tasks (Lou et al., 1989; Sieg et al., 1995; Smith et al., 2006).

## Selective Attention

Selective attention refers to the ability to maintain focus on a stimulus in the presence of other stimuli that serve as distractors (Sohlberg & Mateer, 1989). Therefore, it is presumed that participants who have a better selective attention are also less distractible. Two frequently applied tasks in this test domain are Perceptual discrimination tasks and Flanker tasks (see Table 2). The main difference between these two tasks lies in the characteristics of the stimuli. Perceptual discrimination tasks usually involve degraded (i.e., noisy) stimuli. In contrast, Flanker tasks usually involve pure (i.e., clearly identifiable) stimuli. We show that distinguishing between these two task types is important for clinical research because pure and degraded stimuli seem to evoke different magnitudes of distractibility. We first discuss studies that used Perceptual discrimination tasks, followed by a discussion of studies that used Flanker tasks.

### Perceptual Discrimination Tasks

**Findings From Summary Statistics.** In Friedman-Hill et al.'s (2010) study, children with and without ADHD performed a Picture discrimination task composed of conditions with varying levels of discrimination difficulty (degradation of target pictures) and distractor sa-

**Table 8**
*Summary of Main Findings for Test Domain: Sustained Attention*

| Authors | Tasks | Main behavioral findings |
|---|---|---|
| Collings (2003) | Continuous performance task (CPT). For details, see Table 2. | Boys with ADHD-C made significantly more omission errors than those with ADHD-I or those without ADHD. |
| Baytunca et al. (2018) | Modified continuous performance task (CPT). For details, see Table A1. | The ADHD-only group had similar mean RTs (for correct responses) as the ADHD + SCT group. Both ADHD groups had significantly slower mean RTs (for correct responses) and produced significantly more errors (commission and omission) than the non-ADHD group. The ADHD + SCT group produced significantly more commission errors (but not more omission errors) than the ADHD-only group. |
| Huang-Pollock et al. (2012) | Continuous performance task (CPT). For details, see Table 2. | Children with ADHD show significantly slower and less accurate responses (i.e., lower drift rates) than children without ADHD. |
| Huang-Pollock et al. (2020) | Continuous performance task (CPT). For details, see Table 2. | Comparing performance from first half of blocks of the task with the performance from second half of blocks showed: Children with and without ADHD both showed an increase in the bias towards no-go responses. Compared with children without ADHD, children with ADHD showed additional increases in drift rate for no-go responses over time. |
| Loo et al. (2009) | Continuous performance task (CPT). For details, see Table 2. | The ADHD group and the non-ADHD group did not differ in any behavioral measure (i.e., similar omission and commission errors as well as similar mean RTs for correct responses). |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time; SCT = sluggish cognitive tempo.

**Table 9**
*Summary of Main Findings for Test Domain: Inhibitory Control*

| Authors | Tasks | Main behavioral findings |
|---|---|---|
| Epstein et al. (2011) | Conners' continuous performance task (CCPT). For details, see Table 2. | The ADHD-C and ADHD-I groups both had significantly slower mean RTs (and significantly lower accuracy) than the non-ADHD group. An EGDM analysis showed that the ADHD-C and ADHD-I groups had larger tau values than the non-ADHD group. |
| Baytunca et al. (2018) | Conners' continuous performance task (CCPT). For details, see Table 2. | Only the ADHD-only group had significantly slower mean RTs than the non-ADHD group. The ADHD + SCT group had mean RTs that did not significantly differ from the non-ADHD and ADHD-only group. |
| Wiersema et al. (2006) | Modified conners' continuous performance task (CCPT) composed of blocks with short and long ISIs. For details, see Table A1. | Comparing performance of blocks with long vs. short ISI, children with ADHD had significantly larger differences in both mean RTs and commission errors compared with children without ADHD. Post-hoc analyses showed that some of these group differences were driven by children with ADHD co-morbid oppositional defiant disorder (ODD) or conduct disorder (CD). |
| Mowinckel et al. (2015) | Conners' continuous performance task (CCPT). For details, see Table 2. | Adults with ADHD had significantly slower and less accurate responses (i.e., lower drift rates) than adults without ADHD. |
| Lee et al. (2015) | Modified conners' continuous performance task (CCPT) composed of blocks with either constant ISI or jittered ISI. For details, see Table A1. | For blocks with constant ISI, children with ADHD had larger tau values than children without ADHD. For blocks with jittered ISI, children with ADHD had similar tau values than children without ADHD. |
| Huang-Pollock, Ratcliff, et al. (2017) | Modified conners' continuous performance task (CCPT) with conditions that varied in ISI length and difficulty level. For details, see Table A1. | When ISI was short, children with ADHD had similar drift rates for go trials and a similar bias in starting point towards no-go responses than children without ADHD. When ISI was long, children with ADHD had lower drift rates for go trials and a larger bias in starting point towards no-go responses than children without ADHD. |
| Weigard et al. (2018) | Conners' continuous performance task (CCPT). For details, see Table 2. | Children with ADHD had significantly slower mean RTs (and lower accuracy) than children without ADHD. Moreover, children with ADHD had significantly lower drift rates than children without ADHD. |
| Kingery (2017) | Modified conners' continuous performance task (CCPT). For details, see Table A1. | The children with ADHD had (nonsignificant) higher error rates of omission and commission errors than children without ADHD. |
| Senderecka et al. (2012) | Stop-signal task. For details, see Table 2. | Children with ADHD had slower mean RTs for go trials and slower stop-signal RTs than children without ADHD. Children with and without ADHD had similar error rates, but accuracy was almost at ceiling. |
| Kofler et al. (2018) | Stop-signal task. For details, see Table 2. | No group-specific differences in mean RTs to go trials between children with and without ADHD. |
| Fosco et al. (2018) | Classic stop-signal task (task 1) and a 2-choice task without stop-signals (task 2). For details, see Table A1. | Comparing how model parameters changed between task 1 and 2: All children had unchanged nondecision time components and drift rates but increased boundary separations. Hence, children with and without ADHD likewise adopted a more cautious response strategy in the presence of stop-signals (task 1) than in the absence of any stop-signals (task 2). |
| Weigard et al. (2019) | Stop-signal task. For details, see Table 2. | Children with ADHD had significantly larger sigma and tau values and significantly larger estimates for $P_{TF}$ and $P_{GF}$ than children without ADHD. Moreover, the ADHD-specific increases in $P_{TF}$ and $P_{GF}$ suggest that many of the ADHD-specific slow responses occurred because of failures to initiate control processes. |
| Epstein et al. (2011) | Stop-signal task. For details, see Table 2. | Children with ADHD-C (but not those with ADHD-I) were significantly less accurate and exhibited a significantly larger coefficient of variation (i.e., RT standard deviation/mean RT) than children without ADHD. |
| Tye et al. (2016) | Modified stop-signal task (composed of blocks with slow and fast event rates). For details, see Table A1. | For the slow condition, both ADHD groups (ADHD-only and ADHD + ASD) had significantly slower mean RTs and larger tau values than the non-ADHD group and the ASD group. For the fast condition, both ADHD groups had significantly faster mean RTs and similar tau values to those of the non-ADHD group and the ASD group. |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time; ASD = autism spectrum disorder.

liency (degradation of nontarget pictures surrounding target pictures). Friedman-Hill et al. hypothesized that the efficiency of processes involved in controlling sensory information can be indexed by the performance change across conditions with varying distractor saliency, whereas the efficiency of processes involved in controlling attention can be indexed by the performance change across conditions with varying difficulty level. Table A3 shows that neither accuracy nor mean RTs varied as a function of distractor saliency (neither for the children without ADHD nor for the children with ADHD). Based on these results, Friedman-Hill et al. concluded efficient early-stage control processes for ADHD and non-ADHD. However, it could also be that the processes involved in controlling sensory information were not at all affected by the manipulation of distractor saliency.

The combination of error rate and mean RTs summarized in Table 5 suggests that children with ADHD preferred being accurate over being fast, whereas the children without ADHD preferred being fast over being accurate. This seems an unusual result given that research suggests that children with ADHD usually prefer being fast over being accurate (see for a review: Ziegler et al., 2016).

Based on how performance changed between conditions of varying difficulty levels (see Table 5), Friedman-Hill et al. concluded that distractibility in ADHD arises from insufficient attentional control. However, children with ADHD showed a large heterogeneity in their performance (Table A3), which may be because the ADHD group consisted of an equal number of ADHD-C and ADHD-I. Based on the findings from the test domain "Cognitive Flexibility" and other research (e.g., Ben Shalom et al., 2017; Goth-Owens et al., 2010; Song & Hakoda, 2012), one may expect that participants with ADHD-I, in particular, are most susceptible to distractors. However, the authors did not provide subtype-specific analyses to test this hypothesis.

In the study by Schneidt et al. (2018), adults with and without ADHD performed a Perceptual orientation task (Table A1). Schneidt et al.'s result (see Table 5) is consistent with Friedman-Hill et al. (2010)'s findings discussed above and suggest that ADHD is characterized by slow processing speed. However, slower mean RTs for ADHD could imply that ADHD is characterized by a cautious response strategy, but it could also imply that ADHD is characterized by deficits in processing speed. In the next section, we illustrate how computational models can help to differentiate between different sources.

**Findings From Computational Model Applications.** Mulder et al. (2010) conducted a DDM analysis to compare the performance of children with and without ADHD in a random-dots motion paradigm with accuracy- and speed-emphasized conditions. The results (see Table 5) suggest that children with ADHD (and particularly those with high hyperactivity symptoms) had difficulties adapting a more cautious response strategy in response to changes in instructions (emphasizing accurate vs. fast responding). Moreover, Mulder et al.'s results imply for the findings discussed in the previous paragraphs (e.g., Friedman-Hill et al.; Schneidt et al.) that ADHD-specific slower mean RTs arise from more cautious response strategies rather than from slow processing speed. Particularly, deficits in processing speed would be manifested in longer nondecision time components and/or lower drift rates for ADHD which was not present in Mulder et al.'s study (see Table 5).

The studies discussed in the previous section suggested that ADHD is characterized by a pronounced sensitivity toward distractors, a finding that is further supported by Mulder et al.'s (2010) results. Specifically, children with ADHD needed a higher proportion of coherently moving dots to achieve the same accuracy level as children without ADHD. Moreover, the drift rates of children with ADHD degraded more when difficulty level increased as compared with those of children without ADHD. These results corroborate the previous findings in this section, supporting the view that ADHD is characterized by distractibility.

**Findings From Neurophysiological Measures.** Schneidt et al. (2018), whose behavioral results were discussed earlier, collected EEG-ERPs during a Perceptual orientation task to compare the amplitudes of two components (i.e., EPN: early posterior negativity, and LPP: late positive potential)[8] between adults with and without ADHD. For the high-difficulty condition, adults with ADHD had increased amplitudes in the EPN component compared with those of adults without ADHD. Based on this result, the authors concluded that adults with ADHD could not effectively recruit early-stage attentional filtering processes. This finding is consistent with other studies, suggesting that ADHD is characterized by an inability to recruit prefrontal-parietal networks to resolve conflicting sensory inputs (Cornoldi et al., 2001; Crone et al., 2003; Desimone & Duncan, 1995; Forster et al., 2014; Kastner & Ungerleider, 2001).

For the low-difficulty condition, in Schneidt et al. (2018) found that adults with ADHD had increased amplitudes in the LPP component compared with those of adults without ADHD. Based on this result, the authors concluded that adults with ADHD could not effectively recruit late-stage attentional filtering processes. This result is consistent with the behavioral findings of Friedman-Hill et al. (2010) (discussed earlier), suggesting that ADHD is characterized by deficits in late-stage control processes when task difficulty was low. It remains unclear how the findings from Schneidt et al.'s EEG analyses relate to the findings from behavioral outcome measures.

### *Flanker Tasks*

**Findings From Summary Statistics.** In the study by Johnson et al. (2008), boys with and without ADHD performed a Flanker task (with target arrows pointing in one direction and distractor arrows pointing in the other direction). Johnson et al.'s result (see Table 5) is consistent with the discussed findings of Friedman-Hill et al. (2010; previous section) and Cepeda et al. (2000; test domain: Cognitive Flexibility) and support the view that ADHD is characterized by distractibility. Epstein et al. (2011) used the same Flanker task as Johnson et al. (2008) and found differences between children with ADHD-I, ADHD-C, and without ADHD (including boys and girls). As for the test domain Cognitive Flexibility, there seem to exist subtype-specific differences in this test domain (see Table 5).

Tegelbeckers et al. (2016), Gohil et al. (2017), and Banich et al. (2009) added additional distractors into their Flanker tasks (with target arrows pointing in one direction and distractor arrows pointing in the other direction). Results from these studies suggest that children with ADHD are more sensitive to distractors than children without ADHD (see Table 5). This view is consistent with the findings of Johnson et al. (2008) and Epstein et al. (2011), which used standard Flanker tasks without additional distractors (discussed earlier).

The studies discussed to this point examined results from children. Hasler et al. (2016) administered a Flanker task (with target arrows pointing in one direction and distractor arrows pointing in the other direction) to groups of adults with and without ADHD. Strikingly, all adults (with and without ADHD) had similar mean RTs for both incongruent and congruent trials. This result is inconsistent with those of most other studies and could suggest that the manipulation of stimulus congruency was not strong enough. In the study by Merkt et al. (2013), female college students with

[8] Research suggests that EPN and LPP both serve as indices for distractibility (Hajcak et al., 2012; Milanesi et al., 2007; Schupp et al., 2006).

and without ADHD performed a Flanker task (with even/odd target numbers and congruent/incongruent distractor numbers). Their results (see Table 5) contrast with the initially discussed findings of Johnson et al. (2008). However, Merkt et al.'s results are hard to compare with those of Johnson et al. as many aspects differ between the two studies (e.g., gender and age of participants, target stimuli of the Flanker tasks). Synthesizing the different results suggests that Flanker tasks are not suitable (i.e., produce inconsistently group differences) for the study of ADHD characteristics among adolescents and adults.

**Findings From Computational Model Applications.** Epstein et al. (2011), whose findings were presented earlier, used an EGDM analysis to examine group differences between three groups of children (ADHD-C, ADHD-I, non-ADHD). The ADHD-C group had significantly larger tau values than the non-ADHD and ADHD-I group. This result indicates that the slower mean RTs for ADHD-C (compared with ADHD-I and non-ADHD; see initial discussion at the beginning of this test domain) were primarily attributable to the larger spread in the tails of their RT distribution. However, the EGDM analysis does not allow for conclusions of potential sources that caused the larger spread in the tails of the RT distribution. In contrast, the DDM analysis by Merkt et al. (2013), whose summary statistics were discussed earlier and who also found slower mean RTs for ADHD, suggest that the students with ADHD were characterized by a cautious response strategy (indexed by boundary separation). This is in addition to a poor information integration (indexed by drift rate) and a longer time for perceptual encoding and response execution (indexed by nondecision time component).

Merkt et al. (2013) further found that students with higher scores on a hostility scale had shorter nondecision time components. This result complements the findings of Mulder et al. (2010; section: Perceptual Discrimination Tasks) and suggests that symptoms of hyperactivity and hostility manifest themselves in a short nondecision time component. Interestingly, Merkt et al. (2013) also found that students with higher scores on an anxiety scale had larger boundary separation. This result is consistent with other studies (e.g., White et al., 2010a; see the Introduction section) and suggests that anxiety symptoms manifest in a large boundary separation.

The studies discussed so far used Flanker tasks with distractors and targets occurring always in the same locations on the computer screen. Weigard and Huang-Pollock (2014) applied a DDM analysis to the performance of children with and without ADHD from a Flanker-like search paradigm (Table A1). Their results (see Table 5) suggest that ADHD is characterized by poor information integration and a less cautious response strategy; a finding that is inconsistent with Merkt et al.'s (2013) results as well as with the conclusion derived from studies that used Perceptual discrimination tasks. Specifically, those studies (e.g., Mulder et al., 2010) suggest that ADHD-specific slower mean RTs arise from more cautious response strategies.

Weigard and Huang-Pollock (2014) further found that children without ADHD experienced greater learning effects (i.e., as represented by increases in boundary separation for NC relative to RC trials) than children with ADHD. This result is consistent with Mulder et al.'s (2010) DDM analysis, previously discussed, which showed that children with ADHD had difficulties adapting a more cautious response strategy in response to changes in instructions. Combining the results above suggest that ADHD is characterized by an inflexibility to adjust response strategies when needed (i.e., to speed up learning or to follow changing instructions).

**Findings From Neurophysiological Measures.** Gohil et al. (2017), whose behavioral findings were presented earlier, collected EEG-ERPs during a Flanker task that involved subliminal primes. They assessed group-specific differences in four EEG-ERP components (P1, P3, N1, N2) meant to index early- and late-stage control processes.[9] Children with and without ADHD had similar early-stage components (P1, N1). Hence, the behavioral difference in accuracy between children with and without ADHD seems not to map to a neural difference in the components supposed to index early-stage control processes. Moreover, children with ADHD had significantly larger amplitudes in late-stage components (N2, P3) for incongruent compared with congruent trials. In contrast, children without ADHD had significantly larger amplitudes in late-stage components for congruent compared with incongruent trials.[10] Gohil et al. concluded that children with ADHD had difficulties to recruit late-stage control processes when needed; a finding consistent with previously discussed research that employed Perceptual discrimination tasks (e.g., Friedman-Hill et al., 2010; Schneidt et al., 2018). Like Schneidt et al., Gohil et al. did not find any associations between behavioral measures and neurophysiological measures. Hasler et al. (2016), whose behavioral results were introduced earlier, also collected EEG-ERPs during a Flanker task. Adults with ADHD had significantly lower amplitudes in the P3 component[11] than adults without ADHD (for congruent and incongruent trials). This result, combined with the findings of Gohil et al. (2017) discussed above (see also footnote 13), suggests that ADHD is characterized by an insufficient modulation of late-stage control processes (involved in conflict resolution) as a function incongruency.

In Hasler et al. (2016)'s study, adults with ADHD also had significantly lower power in the alpha and beta frequency bands, presumed to index underactivation particularly in the preparatory stages of the decision process (Engel & Fries, 2010), than adults without ADHD (for congruent and incongruent trials). Hasler et al.'s results are consistent with the theory of the default-mode network,[12] suggesting that ADHD is characterized by insufficient suppression and activation of control processes (i.e., Barkley, 1998; Woods et al., 2002). Interestingly, Hasler et al. found a significant positive correlation between RTs and the power in alpha and beta frequency bands but only for adults without ADHD

[9] Research has shown that the P1 and N1 components are associated with perceptual gating and processes responsible for selective attention (e.g. Herrmann & Knight, 2001). The N2 component is associated with distractibility and its amplitude is enlarged when interference between stimuli is high (Folstein & Van Petten, 2008; Larson et al., 2014). The P3 component is associated with stimulus evaluation, and its amplitude is enlarged when the evaluation process is cognitively less demanding (i.e., low level of conflicting information; Twomey et al., 2015; Verleger et al., 2005).

[10] Moreover, the amplitude of the P3 component was modulated by the prime type (correct vs. incorrect) in children without ADHD. In contrast, the P3 component in children with ADHD did not vary as a function of prime type.

[11] Assumed to measure information integration after stimulus onset; Polich, 2007.

[12] The default-mode network refers to specific brain regions whose activities are low during cognitive performance but high otherwise (e.g., default-mode; Sonuga-Barke & Castellanos, 2007).

(for adults with ADHD, there was no association between RTs and the power in any frequency band.) The findings of Hasler et al. and Gohil et al. both suggest that a mapping between behavioral performance measures and neurophysiological measures is not straightforward. We will address potential issues in the Discussion section: Suggestions for Integrating Neural Measures.

## Working Memory

Most studies define working memory (WM) as a set of cognitive processes that allows an individual to temporarily hold information ready for use in subsequent processing (Baddeley, 2012; Miyake & Shah, 1999; Oberauer et al., 2012, 2018; Unsworth & Engle, 2007). The *N*-back task and the Sternberg task (see Table 2) are tasks that are frequently used for this test domain. In addition to these tasks, manipulations, such as increases in cue-stimulus interval (CSI; or interstimulus interval; ISI), allow researchers to increase the demand on WM in many different cognitive tasks. This is because participants are required to hold information for a greater amount of time when CSI (or ISI) is long rather than short.

### *Findings From Summary Statistics*

Epstein et al. (2011) administered a 1-back task (with letters as target stimuli) to three groups of children (ADHD-C, ADHD-I, and non-ADHD). Their results (see Table 6) are complemented with the findings of Stroux et al. (2016), who administered a 1- and 2-back task (with letters as target stimuli) to adults with and without ADHD. Interestingly, children without ADHD in Epstein et al.'s study were almost as accurate as the adults without ADHD in Stroux et al.'s study (Table A4). In contrast, the children with ADHD in Epstein et al.'s study were much less accurate than the adults with ADHD in Stroux et al.'s study. Hence, ADHD-specific deficits in WM may improve with age.

Kawabe et al. (2018) employed a 1-back task (with playing cards as target stimuli) to boys with ADHD and autism spectrum disorder (ASD) and those without ADHD and ASD. Contrary to the results by Epstein et al. (2011) and Stroux et al. (2016), Kawabe et al. did not find any group differences; neither in mean RTs nor in accuracy. However, Kawabe et al.'s results should be interpreted with caution because the ADHD + ASD group was small (Table A4). The findings from the *N*-back studies discussed so far did not suggest subtype-specific differences in this test domain. Moreover, the studies only found significant group differences in accuracy but not in mean RTs. In Lenartowicz et al. (2014)'s study, children with and without ADHD performed a Sternberg task (with sequentially illuminating dots in different locations of the computer screen). Because Lenartowicz et al. found significant group differences in accuracy and RTs (see Table 6), the Sternberg tasks may be better suited to study ADHD-specific deficits in WM than *N*-back tasks.

### *Findings From Computational Model Applications*

In Weigard and Huang-Pollock's (2017) study, children with and without ADHD performed a modified Sternberg task (see Table 6). Their results suggest that ADHD is characterized by a smaller WM capacity that can be modulated by the degree of cognitive load during the maintenance phase. Moreover, based on the DDM results by Merkt et al. (2013; test domain: Selective Attention) discussed earlier, the difference in nondecision time components between children with and without ADHD (see Table 6) may have been driven by children with ADHD-C.

### *Findings From Neurophysiological Measures*

Stroux et al. (2016), whose behavioral findings were presented earlier, collected EEG-ERPs during 1- and 2-back tasks. Adults with ADHD had significantly lower mean amplitudes in the late-stage component (N2[9]) than adults without ADHD. Most importantly, adults with ADHD had a significantly smaller difference in mean amplitudes between targets and nontargets than adults without ADHD. Stroux et al. concluded that adults with ADHD had difficulties in discriminating between targets and nontargets in an early encoding phase. The findings discussed for the test domain "Cognitive Flexibility" suggest that participants with ADHD-I are particularly susceptible to distractors in early-stage encoding phases. Moreover, Stroux et al.'s result is consistent with the findings from neurophysiological measures discussed for the test domain Selective Attention (Gohil et al., 2017; Hasler et al., 2016). Synthesizing these findings supports the view that ADHD is characterized by an insufficient modulation of control processes in response to their demands (e.g., degree of interference, incongruency).

Stroux et al. (2016) found a significant positive association between the N2 amplitudes for nontargets and accuracy rates for nontargets in correlational analyses. These results contrast with the results from previously discussed studies that did not find any association between neural and behavioral measures (e.g., Hung et al., 2016 for the domain Cognitive Flexibility; Gohil et al., 2017 for the domain Selective Attention). We will elaborate more on these mixed results in the Discussion section: Suggestions for Integrating Neural Measures.

Lenartowicz et al. (2014), whose behavioral findings were presented earlier, examined EEG frequency bands collected during a Sternberg task to distinguish between deficits occurring at different time points of the task (i.e., encoding, maintenance, probe). Midoccipital alpha frequency band (8–12Hz) indexed the efficiency of processing for the encoding stage. Frontal midline theta frequency band (4–7Hz) indexed the efficiency of processing for the maintenance stage. Across all participants, the higher the alpha band power during the encoding phase, the lower the accuracy and the slower the mean RTs. Moreover, children with ADHD had increased alpha band power compared with those of children without ADHD. These results suggest that children with ADHD had less efficient processes during the encoding stage; a finding that is consistent with earlier discussions (i.e., Gohil et al., 2017; Hasler et al., 2016; Stroux et al., 2016) and that supports the view that ADHD is characterized by less efficient early-stage control processes.

Lenartowicz et al. (2014) further found that children with ADHD had increased theta band power compared with those of children without ADHD.[13] These group differences were more pronounced in the low- than in the high-difficulty condition, which suggests that subjects with ADHD had problems to engage WM when the task was cognitively less demanding. This finding is consistent with the default mode network theory (introduced earlier, see also footnote 12), Friedman-Hill et al. (2010)'s results (see test domain: Selective Attention) and supports the view that

[13] Children with ADHD had also decreased alpha-band event-related desynchronization compared with children without ADHD.

ADHD is characterized by problems staying engaged during less demanding tasks.

## Time Perception

An accurate perception of time plays an important role for many cognitive processes (e.g., motor timing of responses, perceptual timing, temporal judgment, temporal foresight, temporal discounting). Deficits in timing processes are therefore implicitly measured in many different cognitive tasks such as delay discounting tasks, motor timing tasks, and coordination tasks (e.g., Barkley, 1997b; Marx et al., 2017; Nigg & Casey, 2005). The focus for this test domain lies on perceptual timing tasks (i.e., Time reproduction tasks and Time differentiation tasks; Table 2) that provide an explicit measure of participants' ability to reproduce and to discriminate between different amounts of time.

### *Findings From Summary Statistics*

Marx et al. (2017) found that boys with ADHD had poorer performance than boys without ADHD in a variety of perceptual timing tasks (see Table 7). These results are complemented with the findings of Valko et al. (2010) who administered a Time reproduction task and a Time differentiation task (Table A1) to adults and children with and without ADHD. Their findings (see Table 7) suggest that ADHD is characterized by abnormal time processing and ADHD-specific age-related shifts in accuracy-speed tradeoffs. In particular, age-related increases in accuracy (accompanied by decreases in mean RTs) were larger in the non-ADHD group than in the ADHD group. Hence, ADHD-specific deficits in time perception may improve with age.

### *Findings From Computational Model Applications*

Shapiro and Huang-Pollock (2019) compared performance of children with and without ADHD in a Time differentiation task with a modified AAM analysis (i.e., time-adaptive, opponent poisson model). Their results are consistent with Valko et al.'s (2010) findings and suggest that children with ADHD had more difficulties discriminating between short and long durations than children without ADHD. Shapiro and Huang-Pollock also found that children with and without ADHD did not significantly differ in their estimated bisection point,[14] but children with ADHD exhibited a starting point bias for assigning tones into the "short duration" category. It seems unclear how the group difference in the starting point should be interpreted given that there was no group difference in the bisection point. Intuitively, a bias for assigning tones into the "short duration" category should be reflected in a lower bisection point given that the drift criterion[15] remained constant.

### *Findings From Neurophysiological Measures*

None of the studies discussed in this section collected neuronal measures during the task. However, the study by Marx et al. (2017), discussed earlier, suggests that ADHD-specific timing deficits arise from multiple components, namely perceptual stimulus encoding and reproducing of the stimulus duration. This hypothesis is testable with the joint application of sequential sampling models and the collection of EEG measures (see Discussion section: Suggestions for Integrating Neural Measures).

## Sustained Attention

Sustained attention describes the ability to maintain attention over an extended period of time (Huang-Pollock et al., 2012). One of the most applied tasks in this test domain is the CPT (see Table 2). In the CPT, participants are instructed to detect rare target stimuli (10% to 25%) in a series of rapidly presented nontarget stimuli (90% to 75%). Measures of omission and commission errors, as well as mean RTs are presumed to index the ability to sustain attention (e.g., Nichols & Waschbusch, 2004). There are several review articles that have synthesized a large number of studies in this test domain (Boonstra et al., 2005; Hasson & Fine, 2012; Huang-Pollock et al., 2012; Losier et al., 1996; Nichols & Waschbusch, 2004). Therefore, we focus on studies that included analyses of ADHD subgroup-specific differences or DDM analyses.

### *Findings From Summary Statistics*

In a study by Collings (2003), boys with and without ADHD performed a CPT. Baytunca et al. (2018) also applied a CPT and their results extend Collings' findings with the examination of ADHD subgroups different from the subtypes (ADHD-C, ADHD-I). Specifically, Baytunca et al. divided children with ADHD into subgroups, either ADHD-only or ADHD + SCT based on parent- and teacher-rated scores on the slow cognitive tempo scale (McBurnett et al., 2001). Whereas Collings found group-specific differences in omission errors, Baytunca et al. found group-specific differences in commission errors and mean RTs (see Table 8). However, Baytunca et al.'s and Collings' results are hard to compare because of differences in gender and subgrouping (Table A6). Nevertheless, both studies provide evidence for ADHD endophenotype-specific differences in this test domain.

### *Findings From Computational Model Applications*

Huang-Pollock et al. (2012) performed a meta-analysis with the DDM including 12 clinical studies that administered CPTs (with visual stimuli only) and that reported accuracy, mean RTs, and RT variances. Children with ADHD had significantly lower drift rates (but similar boundary separation and nondecision time components) than children without ADHD. The starting point was fixed symmetrically between the boundaries. Recent DDM analyses of CPTs (and Conners' Continuous Performance Tasks [CCPTs]) have shown biases in starting points and in drift rates (Huang-Pollock, Ratcliff, et al., 2017; Ratcliff et al., 2018). Therefore, the meta-analysis by Huang-Pollock et al. needs to be updated. Moreover, the result that children with ADHD were characterized by low drift rates is only partially consistent with DDM applications discussed in other test domains (i.e., Cognitive Flexibility, Selective Attention, Working Memory). For instance, findings suggest that ADHD-C (and ADHD with comorbid externalizing symptoms) are characterized by shorter nondecision time components and a rigid response strategy (e.g., Merkt et al., 2013; Metin et al.,

[14] The bisection point represents the duration of a tone at which a participant's accuracy for assigning a stimulus into either the "short" or "long duration" category is at chance (Church & Deluty, 1977).

[15] The drift criterion is the dividing point between the mean drift rate towards the "short duration" response category and the mean drift rate towards "long duration" response category.

2013; Mulder et al., 2010; Salum et al., 2014; Weigard & Huang-Pollock, 2017).

If ADHD is characterized by an inability to *sustain* attention, one would expect performance of participants with ADHD to decline more over time as compared with that of participants without ADHD. To test this hypothesis, one would need to divide trials into different time blocks (e.g., for a task with 40 trials: one block containing the first 20 trials, and one block containing the last 20 trials), estimate separate model parameters for the different time blocks, and compare them with each other (e.g., Huang-Pollock et al., 2020: Table 8). However, Huang-Pollock et al. (2012) reported that most studies did not provide measures of mean RTs or accuracy as a function of blocks in the task. Hence, this test domain seems difficult to explore with computational models applied to existing data sets (see also Discussion section: Suggestions for Applying Computational Models).

### Findings From Neurophysiological Measures

Loo et al. (2009) administered a CPT, in conjunction with EEG, to groups of adults with and without ADHD (see Table 8). Loo et al. divided the CPT into a first, middle, and last block to test for group-specific differences in alpha and beta band power in each of these blocks. The ADHD and non-ADHD groups had similar values in alpha band power for the first block. For the last relative to the first block though, the ADHD group had a significantly smaller decrease in alpha band power as compared with the non-ADHD group. These results suggest that adults with ADHD had more difficulties to maintain attention over time (because a larger decrease in alpha band power is associated with a larger increase in cortical activity associated with cognitive processing). This finding is consistent with the default mode network theory (introduced earlier) and is also supported by the similar results discussed previously for the test domains Selective Attention and Working Memory (e.g., Friedman-Hill et al., 2010; Hasler et al., 2016; Lenartowicz et al., 2014).

## Inhibitory Control

Inhibitory control is often operationalized as the efficiency of cognitive control processes to withhold ongoing actions in the presence of new information (Logan et al., 1984; Raiker et al., 2012). CCPTs and Stop-signal tasks are frequently used for this test domain (see Table 2). The Stop-signal task is considered to measure “response inhibition” because participants are required to stop their ongoing responses on trials that introduce a signal after stimulus onset. The standard CCPT (also known as the go/no-go task) includes more go trials (75% to 90%) than no-go trials (10% to 25%). Conversely, the CPT includes more no-go than go trials (see previous section: Sustained Attention). Therefore, participants need to frequently respond, but then to inhibit this response pattern on the rare no-go trials. In what follows, we first discuss studies that used CCPTs and then studies that employed stop-signal tasks.

### Conners’ Continuous Performance Tasks

**Findings From Summary Statistics.** Results remain mixed whether CCPTs elicit differences between participants with and without ADHD (Halperin et al., 1992; Klee & Garfinkel, 1983; Koelega, 1995; Rovet & Hepworth, 2001; Shapiro & Garfinkel, 1986; Zahn et al., 1991). Likewise, many studies that administered CCPTs did not find evidence for subtype-specific differences, but evidence remains mixed (Baytunca et al., 2018; Edwards et al., 2007; Egeland, & Kowalik-Gran, 2008; Epstein et al., 2011; Scheres et al., 2001). For instance, Epstein et al. (2011) administered a CCPT to three groups of children (non-ADHD, ADHD-C, ADHD-I). In contrast, Baytunca et al. (2018) administered a CCPT to children with and without ADHD. Children with ADHD were subgrouped into either ADHD-only or ADHD + SCT based on parent- and teacher-rated scores on the slow cognitive tempo scale (McBurnett et al., 2001). Similar to Epstein et al.’s result, both ADHD groups made significantly more errors than the non-ADHD group (see Table 9). However, Epstein et al. found also significant group differences in accuracy while Baytunca et al. did not. The studies by Epstein et al. and Baytunca et al. illustrate that comparisons across study results are difficult. First, the studies used different criteria to define ADHD subtypes although both studies subtyped ADHD for their primary analyses. Hence, divergent results could be attributable to differences in sample characteristics. Second, the studies used different versions of the CCPT (e.g., different types of stimuli, Table A1). Hence, divergent results could also be attributable to dissimilarities in task specifics.

To produce failures in response inhibition, ISI is sometimes varied across conditions. By doing so, it is reasoned that a short ISI produces more commission errors and faster RTs when attention is “on task” but produces more omission errors and slower RTs when attention is “off task” (Chee et al., 1989; Davis, 1957; Kantowitz, 1974; McGrath et al., 1968). For this reason, the CCPT was thought to hold promise not only in the diagnosis of ADHD, but also in the distinction between different subtypes of ADHD (Edwards et al., 2007; Scheres et al., 2001). Specifically, in conditions with short relative to long ISIs, participants with ADHD-C (or ADHD-H) were expected to produce faster RTs and more commission errors than participants with ADHD-I, who were expected to produce slower RTs and more omission errors. The studies discussed thus far did not examine subtype-specific differences as a function of ISI. In contrast, Wiersema et al. (2006) did examine performance in a CCPT that involved blocks with short and long ISIs. Consistent with the hypothesis above, children with ADHD and pronounced hyperactivity-impulsivity symptoms are characterized by faster RTs and more commission errors in blocks with short ISI (see Table 9). It remains to be determined whether participants with ADHD-I are characterized by slower RTs and more omission errors in blocks with long ISIs.

**Findings From Computational Model Applications.** Mowinckel et al. (2015) conducted a DDM meta-analysis of nine studies that administered a CCPT to adults with and without ADHD. Mowinckel et al.’s results (see Table 9) are consistent with the results by Huang-Pollock et al.’s (2012) meta-analysis described in the test domain Sustained Attention. However, DDM applications that we discussed in other test domains (e.g., Cognitive Flexibility, Selective Attention, Working Memory) suggested that different ADHD endophenotypes expressed characteristics in distinct model parameters (e.g., Merkt et al., 2013; Metin et al., 2013; Mulder et al., 2010; Salum et al., 2014; Weigard & Huang-Pollock, 2017).

Lee et al. (2015) hypothesized that the ADHD-specific increases in tau values found in CCPTs (e.g., Epstein et al., 2011) indicate failures in inhibitory control processes. They administered a modified CCPT (composed of blocks with either constant ISI or jittered

ISI) to children with and without ADHD and then applied an EGDM analysis. Their results (see Table 9) are consistent with their hypothesis above. However, the explanation provided by Lee et al. rests on the concept of "Sustained Attention." Specifically, to explain ADHD-specific larger tau values for blocks with constant ISI, Lee et al. argued that jittering ISI helped children with ADHD to maintain their attention (which otherwise decayed faster as evident by the larger tau values in the blocks with constant ISI). This explanation rests on the definition of "Inhibitory Control" as maintaining attention (i.e., withholding the influence of potential distractors on ongoing actions).

The hypothesis usually examined with CCPTs (i.e., participants with ADHD produce particularly more commission errors when ISI is short rather than long) could not be tested by Lee et al. (2015), because the different block types involved ISIs of similar lengths (Table A1). A paradigm related to Lee et al. (2015)'s study design, but used to test the hypothesis associated with the test domain "Inhibitory Control," was introduced by Huang-Pollock, Ratcliff, et al. (2017). Children with and without ADHD performed a modified CCPT (with conditions that varied in ISI length and difficulty level), and their performance was analyzed with a DDM application. Huang-Pollock et al.'s findings (see Table 9) question whether ADHD is characterized by failures in "Inhibitory Control." This is because failures in "Inhibitory Control" would not be expected to result in larger biases toward no-go responses.

The results by Huang-Pollock, Ratcliff, et al. (2017) differ from the findings of Lee et al. (2015). Specifically, whereas performance of the ADHD group did not vary as a function of ISI in Lee et al.'s study, performance of the ADHD group did vary as a function of ISI in Huang-Pollock et al.'s study (see Table 9). Importantly, only the performance of children with ADHD varied with ISI (the performance of children without ADHD was similar across ISI conditions). This result is consistent with findings discussed previously (test domains: Selective Attention, Sustained Attention), suggesting that ADHD-specific characteristics can be found when one focuses on how performance changes across multiple conditions.

Applying an AAM analysis (using the linear ballistic accumulator model, LBA, Brown & Heathcote, 2008) to the data from children with and without ADHD from a similar numerosity discrimination task used by Huang-Pollock, Ratcliff, et al. (2017); Weigard et al. (2018) found additional support for the conclusion above (see Table 9). Moreover, Weigard et al.'s results, combined with the findings of Friedman-Hill et al. (2010; see test domain: Selective Attention), suggest that manipulating difficulty levels across conditions represent a sensitive alternative to manipulations of ISIs to study clinical characteristics of ADHD.

**Findings From Neurophysiological Measures.** Kingery (2017) compared EEG–ERP components (P3, Pz, P4) in an auditory CCPT between children with and without ADHD with an EGDM analysis (see Table 9). Each child's RT distribution for correct responses was subdivided into terciles for fast, medium, and slow RTs.[16] Slow RT terciles were associated with decreased peak amplitudes (which could be attributable to averaging over a longer time interval) and lower AUC, but these changes in EEG activity (i.e., peak amplitude, latency and AUC) were similar for children with and without ADHD. Wiersema et al. (2006), whose behavioral results were presented earlier, also found a significant association between RTs and P3 amplitudes (for all participants). Specifically, the difference in mean RTs between blocks with short and long ISIs was significantly associated with the difference in P3 amplitudes between those two block types. These results suggest that P3 components are associated with RTs but not with accuracy. Wiersema et al. (2006) also found that the frequent commission errors of children with ADHD (particularly those with ADHD comorbid oppositional defiant/conduct disorder) were significantly associated with smaller amplitudes in the N2 components. This result is consistent with the finding of Stroux et al. (2016; test domain: Working Memory), who used *N*-back tasks and who found a significant positive association between the N2 amplitudes and accuracy rates for nontargets (but not for targets). Synthesizing all results suggest that N2 components are associated with accuracy but not with RTs.

The above findings suggest that earlier EEG-ERP components covary with accuracy, whereas later EEG-ERP components covary with RTs. However, there seem to exist other latent variables that affect these associations because some of the previously discussed studies did not find any association between neural and behavioral measures (e.g., Hung et al., 2016 for the domain Cognitive Flexibility; Gohil et al., 2017 for the domain Selective Attention), whereas other studies found that other neural components also affect performance (Durston et al., 2003; Groom et al., 2010; Kingery, 2017; Van De Voorde et al., 2010; Wiersema et al., 2005, 2006; Zhang et al., 2009). For instance, Durston et al. (2003) found that children with ADHD had decreased activation of frontostriatal regions and increased activation of more diffuse network regions for go trials that followed no-go trials.

### *Stop-Signal Task*

**Findings From Summary Statistics.** Numerous studies found that participants with ADHD had slower RTs for go trials with intermittent Stop-signals as compared with participants without ADHD (Alderson et al., 2007; Lipszyc & Schachar, 2010; Martel et al., 2007; Nigg, 1999; Senderecka et al., 2012; Willcutt et al., 2005). Despite the above findings, multiple other studies suggest that slow RTs in Stop-signal tasks are not specific to ADHD but rather characterize a broader set of clinical disorders (Arabzadeh et al., 2014; Hughes et al., 2012; Lipszyc & Schachar, 2010). For instance, Kofler et al. (2018) and Fosco et al. (2019) both studied differences between children with and without ADHD in a Stop-signal task and they did not find any differences in mean RTs for go trials. However, the groups without ADHD included not only neurotypical children but also children with psychiatric disorders other than ADHD. Hence, children with ADHD and those with other disorders seem to share clinical, ADHD-unrelated, characteristics that result in similar behavioral differences.

**Findings From Computational Model Applications.** ADHD-specific slow RTs in Stop-signal tasks can have different reasons. For instance, participants may adapt a cautious response strategy in the presence of stop-signals. Alternatively, participants

[16] For each tercile, EEG-ERPs (P3, P4) were averaged across all epochs between stimulus onset and the following 900ms to identify peak amplitude and latency. Linear mixed models were estimated with tercile RTs as independent variables for amplitude, latency, and area under the curve (AUC).

may process information at a slow rate because of the increased cognitive demand. Fosco et al. (2019), whose summary statistics were discussed above, showed that a DDM analysis can help to disentangle the extent to which slow RTs are attributable to response cautiousness, deficits in information processing and/or latency of perceptual encoding and motor execution. Their results (see Table 9) question whether the Stop-signal task measures inhibition control. Rather, their findings suggest that changes in response strategies could account for slower RTs in the presence of stop-signals. It would have been interesting to examine in Fosco et al.'s study whether measures on anxiety were associated with larger boundary separation as found by Merkt et al. (2013; test domain: Selective Attention).

Another explanation on the constructs measured in Stop-signal tasks is provided by Weigard et al. (2019). They argued that slower RTs in the presence of stop-signals could also stem from inhibitory control processes that were not activated at all. To test this hypothesis, Weigard et al. administered a Stop-signal task to children with and without ADHD. They then applied a modified EGDM analysis, which provided the common EGDM parameters ($\mu$, $\sigma$, $\tau$) for the RT distributions of correct responses (go responses to go trials; $\mu_{\text{go-match}}$, $\sigma_{\text{go-match}}$), for those of commission errors (go responses to no-go trials; $\mu_{\text{go-mismatch}}$, $\sigma_{\text{go-mismatch}}$),[17] and additional estimates for the probability that the stop-signal did not trigger an inhibition process ($P_{TF}$; commission errors), and the probability that the go stimulus did not trigger a go response ($P_{GF}$; omission errors). ADHD-specific RT distributions were characterized by a faster rise in the leading edge (indexed by sigma) and a larger spread in the tails (indexed by tau) relative to non-ADHD.

One may wonder whether ADHD endophenotype-specific differences can be found in this test domain. Epstein et al. (2011) administered a Stop-signal task to three group of children (non-ADHD, ADHD-C, ADHD-I) and applied an EGDM analysis to test for subtype-specific differences in the Stop-signal task. There were no significant group differences in EGDM parameters, which contrasts with the above findings of Weigard et al. (2019). Tye et al. (2016) examined whether a modified Stop-signal task, in conjunction with an EGDM analysis, can be used to discriminate between ADHD and autism spectrum disorder (ASD). The Stop-signal task was employed to a group of boys with ASD, a group of boys with ADHD only, a group of boys with ADHD and ASD (ADHD + ASD), and a group of boys without ADHD (non-ADHD group). Tye et al.'s results (see Table 9) suggest that Stop-signal tasks can be used to distinguish between different ADHD endophenotype-specific characteristics. Moreover, the finding (Table A7) that $\tau$ values were similar between ADHD and control groups but substantially larger when ISI was long is consistent with the findings by Lee et al. (2015). However, as explained in the previous section "Sustained Attention," $\tau$ values seem to index a measure more related to "Sustained Attention" than "Inhibitory Control."

**Findings From Neurophysiological Measures.** Senderecka et al. (2012), whose behavioral findings were presented earlier, collected EEG-ERPs during a Stop-signal task. Relative to children without ADHD, children with ADHD showed smaller differences between correct and error responses on the stop-signal trials in the amplitudes of the P3 component (meant to index successful response inhibition). Similar results were found in other studies (Johnstone et al., 2007; Overtoom et al., 2003; Wessel & Aron, 2015). For instance, a study by Wessel and Aron (2015) suggested that the latency of the P3 component indexed the temporal onset of response inhibition processes and that the P3 latency onset was highly correlated with stop-signal RTs. These results are consistent with the findings from EEG studies discussed previously and that suggested associations between P3 components and RTs (e.g., Hung et al., 2016 for the domain: Cognitive Flexibility; Gohil et al., 2017 for the domain: Selective Attention; Wiersema et al., 2006 for CCPTs). Senderecka et al. (2012) also found that, relative to children without ADHD, children with ADHD showed a larger amplitude and a longer latency in the N2 component for correct responses and smaller ERN-Pe complexes (associated with the detection of error responses). Similar results were found in EEG studies discussed previously (test domain Working Memory: Stroux et al., 2016; test domain CCPTs: Wiersema et al., 2006). The above results suggest the existence of ADHD-specific neural differences. However, the neural characteristics of ADHD remain unclear as studies propose multiple components and concepts to find ADHD-specific characteristics.

## Discussion

In the next subsection, we summarize the findings for each test domain. We then provide suggestions for: the improvement of cognitive testing (subsection 2), the consideration of critical aspects when applying computational models (subsection 3), and the integration of neurophysiological measures (subsection 4) and sample characteristics (subsection 5) into cognitive testing for ADHD. In the final subsection, we provide concluding remarks (e.g., limitations of this review). Table 10 lists the most important messages of this article (i.e., recommendations for cognitive testing, computational modeling, and integrating neurophysiological measures) which are general applicable.

### Summary of Findings Across Test Domains

#### *Cognitive Flexibility*

Paradigms reviewed for this test domain required participants to switch between different features of the same stimulus (i.e., feature-switch paradigms) or between different tasks (i.e., task-switch paradigms). Studies that utilized task-switch paradigms consistently found large group differences in switch costs between children with ADHD (mostly with ADHD-C) and those without ADHD. The type of switch costs (i.e., global or local switch costs in terms of accuracy, mean RTs, or both) and the size of effect varied across studies. We showed that mixed evidence can be reconciled when considering differences in the specifics of task-switch paradigms across studies (e.g., cue-stimulus intervals, predictability of task-switches, similarity of tasks involved in the task-switch paradigm). Studies that utilized feature-switch paradigms found differences between *DSM*-defined ADHD subtypes (i.e., ADHD-C and ADHD-I). ADHD-C was characterized by a slow processing speed, whereas ADHD-I was characterized by a pronounced local-oriented encoding style (i.e., in Navon tasks: ADHD-I showed greater interference from local stimuli when asked to process at a global level as compared with non-ADHD; in

[17] Tau ($\tau$) was kept constant across the two RT distributions.

**Table 10**
*Take-Home Messages*

| Suggestions for improving cognitive tests for ADHD | Suggestions for applying computational models | Suggestions for integrating neurophysiological measures |
|---|---|---|
| • Incorporating sample characteristics (e.g., ADHD subgroups, gender) can help to account for the heterogenous performance observed among ADHD. | • Parameters from sequential sampling models (but not those from ex-Gaussian distribution models) have well established psychological interpretations. | • Collecting EEG measures without theoretical foundation often biases investigators to focus on significant results only. |
| • Considering that "Cognitive flexibility" is a promising test domain to study differences between ADHD endophenotypes. | • Sequential sampling models simultaneously incorporate reaction time distributions and corresponding accuracy values, while ex-Gaussian distribution models account only for reaction time distributions. | • Many studies focus on latency and peak amplitude when characterizing EEG-ERPs. However, it can be beneficial to measure the onset or offset of a component rather than the peak. Measures like "fractional area latency" are particularly suitable for making comparisons with RTs. |
| • Improving the current understanding of cognitive concepts measured with cognitive tasks is important. | • Sequential sampling models allow to decompose conventional performance measures into cognitive components that can be separately studied. | • The conjoint application of computational models and neurophysiological measures could provide explanations for cases in which group differences were only evident in neurophysiological measures, but not in behavioral measures (or vice versa). |
| • Considering that tasks and cognitive constructs are often interchanged in inconsistent ways. | • Tasks often need adjustments to be applicable for computational models. For instance, sufficiently high error rates (>10% per task) and number of trials (>50 per condition) are needed to accurately estimate model parameters. | • Different ADHD phenotypes may have deficits that affect their decision process at different time points. The time dynamics of the neural pattern become quantifiable and psychologically interpretable with joint modeling approaches of behavioral and neural measures. |
| • Considering that ADHD characteristics are more likely to be observed when tasks are difficult. | • Computational models need to adequately fit the data before their parameters can be legitimately used to interpret results. Goodness of fit should be checked not only with the use of critical values (e.g., Chi-square), but also by deriving predictions and by plotting predictions against data. | |
| • Considering that tasks need to be sensitive to detect subtle clinical characteristics. For instance, a task with multiple conditions can provide insights into how participants adapt to contextual changes (illustrating unique mechanisms of their decision process). | • Correlational analyses between model parameters allow to detect if model parameters likely do not index different components. This can be particularly the case for very easy tasks with pure stimuli (e.g., CCPTs) but is less likely for difficult tasks (e.g., task-switch paradigms) | |
| • It is unlikely that a single diagnostic task can account for multiple ADHD endophenotypes. Instead, a battery of tasks should be designed that focuses on social and cognitive characteristics and that incorporate findings from other research areas (e.g., cognitive psychology for cognitive tasks, behavioral economics for social cognitive tasks). | | |

*Note*. ADHD = attention-deficit/hyperactivity disorder.



Attentional blink tasks: ADHD-I were better able to detect probe letters than ADHD-C and non-ADHD).

DDM analyses suggested ADHD to be characterized by lower drift rates and longer nondecision time components (compared with non-ADHD). These results suggest impairments in information integration and in the activation of early- and late-stage control processes. Ging-Jehli and Ratcliff (2020) recently illustrated with a DDM application to a task-switch paradigm that DDM parameters can be used to index distinct control processes. They showed that the nondecision time component can index early-stage control processes (involved in reconfiguring the cognitive system for task switches), whereas the drift rate can index late-stage control processes (involved in resolving any interference that arises from performing multiple tasks). Hence, task-switch paradigms in conjunction with computational modeling seems promising for the study of ADHD characteristics. Moreover, studies indicated that the higher the severity of ADHD symptoms, the lower the drift rates and the longer the nondecision time components. This suggests that model parameters could be used to approximate a spectrum of ADHD, considering it a dimensional disorder rather than a categorical disorder. This notion is supported by findings from neuroimaging, behavioral genetics and taxonomic studies (Carson, 1991; Clark et al., 1995; Coghill & Sonuga-Barke, 2012; Larsson et al., 2012; Marcus et al., 2012). Acknowledging ADHD as a dimensional disorder implies that participants with a clinical diagnosis of ADHD differ from those with moderate or mild ADHD symptoms in the degree of severity on a continuous spectrum of severity. In contrast, regarding ADHD as a categorical disorder implies that participants with a clinical diagnosis of ADHD differ not only quantitatively from normality but they also lie outside any variation in the normal range. The results from sequential sampling models point toward a spectrum of ADHD, illustrating specific biases in the decision processes of participants with ADHD that can lie in the variation of the normal range. Hence, sequential sampling models such as the DDM represent an alternative approach to discover dysfunctionalities, can account for individual differences and heterogeneity in ADHD, and can refine the cognitive characteristics of ADHD endophenotypes. However, on review of the DDM analyses of some clinical studies, the findings should be interpreted with caution (e.g., unsuccessful manipulations of difficulty levels; a very low number of trials which compromises parameter estimation).

Brain imaging studies (Fink et al., 1996; Song & Hakoda, 2012; Yeo et al., 2003) relate biases in local information processing in ADHD-I to dysfunctions (i.e., reduced cortical and subcortical volumes) in the right hemisphere. Further evidence from neurophysiological measures suggested differences between participants with and without ADHD for multiple EEG-ERP components. Sequential sampling models could be used to link neuronal measures to specific cognitive components, assigning a psychological interpretation to the different ERP components (Turner et al., 2017).

### *Selective Attention*

Studies were organized based on whether they employed Perceptual discrimination tasks (involving degraded stimuli) or Flanker tasks (involving undegraded stimuli). Research that employed Perceptual discrimination tasks found that participants with ADHD (children and adults) were more distractible than participants without ADHD. We discussed examples of mixed findings and highlighted that significant heterogeneity exists in performance among participants with ADHD. However, most studies did not account for ADHD subtypes or any comorbidities. We showed that some of the mixed evidence could be reconciled when considering characteristics such as gender, ADHD subgroups, and comorbidities. For instance, numerous studies suggest that ADHD-I seems to be characterized by impairments in processes involved in filtering relevant from irrelevant information (e.g., Carlson et al., 1986; Goth-Owens et al., 2010; Song & Hakoda, 2012; Weiler et al., 2002). Studies that employed Flanker tasks showed that participants with ADHD were more sensitive to distractors (irrespective of whether distractors were relevant, irrelevant, subliminal, or salient) than participants without ADHD. Moreover, results from studies that used Flanker tasks seemed first to contradict the results from studies that used Perceptual discrimination tasks. However, these contradictory results can be reconciled when considering that Flanker tasks imposed less difficulty (as shown by accuracy above 95%) than Perceptual Discrimination tasks (as shown by accuracy between 65% and 90%). It further implies that the stimulus degradation (pure vs. degraded stimuli) may be an important distinction for clinical research, because pure and degraded stimuli seem to evoke different magnitudes of distractibility. Moreover, evidence suggests that participants with ADHD were less distractible when task difficulty was high rather than low; or when the interstimulus interval (ISI) was short rather than long.

DDM applications to Perceptual discrimination tasks showed that particularly individuals with ADHD and a high degree in hyperactivity have deficits in adjusting their response strategy when asked to make accurate rather than fast responses (i.e., as indexed by the model parameter boundary separation). DDM applications to Flanker tasks found a positive association between anxiety and boundary separation (i.e., indexing cautiousness of response strategy) and a negative association between hostility and nondecision time component (indexing the time for perceptually encoding and response execution) for all participants (with and without ADHD). Moreover, ADHD was characterized by lower drift rates (compared with non-ADHD). Like for the test domain Cognitive Flexibility, ADHD-related deficits in drift rates were linearly related to symptom severity. EGDM analyses of Flanker tasks found that children with ADHD-C had significantly larger tau values (indicating a higher proportion of slow responses) than children with ADHD-I or those without ADHD. To date, the psychological interpretation of EGDM parameters such as tau (e.g., index for lapses of inattention, slowed processing, deficits in motor output) remain unclear (see Table 3).

Studies that examined neurophysiological measures support the view that ADHD is characterized by a pronounced degree of distractibility (Libera & Chelazzi, 2006; Mason et al., 2003; Tegelbeckers et al., 2015; Weissman et al., 2002). For instance, studies that utilized functional brain imaging (fMRI) showed that boys with ADHD had enhanced neural activity when presented with unexpected, irrelevant stimuli as compared with boys without ADHD (Banich et al., 2009; Tegelbeckers et al., 2015). Studies that utilized EEG-ERPs showed that participants with ADHD processed and filtered sensory inputs differently than participants without ADHD (Gohil et al., 2017; Hasler et al., 2016; Schneidt et al., 2018). There are several hypotheses for this test domain about the psychological meaning of EEG-ERP components such as EPN and LPP. With sequential sampling models, one could link these neuronal measures to specific cognitive components, assigning a psychological interpretation to those neural constructs (e.g., Palestro et al., 2018; Philiastides et al., 2006; Ratcliff, Sederberg, et al., 2016; Schubert et al., 2019; Van Vugt et al., 2012). For instance, in the framework of sequential sampling models, EPN may be associated with nondecision time components, whereas LPP may be associated with drift rates. This represents an alternative approach to discover dysfunctionality. The aim would be to account for individual differences and heterogeneity in ADHD and refine the cognitive characteristics of ADHD endophenotypes. In particular, the joint modeling of behavioral and neural data may help to determine whether distractibility is caused by increased interference in sensory processing, decreased capability to activate executive control processes, or impaired feedback loops between executive control processes and networks that process sensory inputs (see for a discussion of these latest approaches: Turner et al., 2017).

### Working Memory

*N*-back tasks and Sternberg tasks were paradigms frequently used in this test domain. Studies that employed *N*-back tasks showed that participants with ADHD (children and adults) had poorer performance (as evidenced by lower accuracy values but similar mean RTs) than participants without ADHD (e.g., Epstein et al., 2011; Stroux et al., 2016). However, a study that focused on boys without any mental health disorders and those with ADHD and autism spectrum disorder (ASD) did not find any group-specific differences, neither in accuracy values nor in mean RTs (Kawabe et al., 2018). A study that employed modified Sternberg tasks by introducing a second distractor task during the maintenance phase of the Sternberg task found that children with ADHD were slower, less accurate, and exhibited a higher RT variability than children without ADHD. Modified Sternberg tasks seem particularly suited to study WM deficits because it can be used to address whether participants with ADHD had poorer performance in WM tasks because of deficits in the perceptual encoding of stimuli (encoding phase) or because of deficits in maintaining the information in WM (maintenance phase).

In the framework of sequential sampling models, deficits during the encoding phase of a WM task would lead to longer nondecision time components for ADHD. In contrast, deficits during the maintenance phase of a WM task would lead to lower drift rates for ADHD. DDM applications to modified Sternberg tasks suggested ADHD to be characterized by deficits in both, perceptual encoding (as evidenced by longer nondecision time components) and information maintaining (as evidenced by lower drift rates). Past EGDM applications to 1-back tasks suggested ADHD (i.e., both ADHD-C and ADHD-I) to be characterized by large tau values (i.e., higher proportion of slow responses).

Research proposes that deficits in WM are a characteristic for ADHD (Buzy et al., 2009; Lenartowicz et al., 2014; Weigard & Huang-Pollock, 2017; Willcutt et al., 2005). The underlying neurophysiological components that lead to WM deficits remain a topic of debate. Some studies suggest that WM deficits are a consequence of limited prefrontal capacities (e.g., Friedman-Hill et al., 2010; Lavie & De Fockert, 2003). Other studies suggest that WM deficits are attributable to impairments in controlling attention (e.g., Friedman-Hill et al., 2010; Huang-Pollock et al., 2006) or to biased processing of information (e.g., Lenartowicz et al., 2014). Studies (Lenartowicz et al., 2014; Stroux et al., 2016) that collected EEG measures during task performance suggested that ADHD is characterized by deficits in perceptual encoding only. This finding could result from an insufficient deactivation of the default mode network resulting in a delayed start of stimulus encoding and a lower refreshing rate of items in WM. This hypothesis could be tested in a paradigm with a joint modeling approach of neural and behavioral responses (Palestro et al., 2018; Ratcliff, Sederberg, et al., 2016; Turner et al., 2017; Van Vugt et al., 2012).

### Time Perception

We focused on time discriminations tasks such as time reproduction tasks and time differentiation tasks. For both task types, ADHD children and adults displayed abnormal temporal processing (i.e., systematically overpredicting elapsed time intervals). These results are consistent with the findings from studies in related test domains (Barkley et al., 1997; McInerney & Kerns, 2003; Smith et al., 2008). For instance, participants with ADHD showed greater temporal discounting than participants without ADHD in different delay discounting tasks (Barkley et al., 2001; Bitsakou et al., 2009). Future research is needed to examine to what extent abnormal temporal processing influences performance in these other tasks. To date, studies have not investigated any subtype-specific differences in this domain.

Different theoretical explanations have been proposed to account for the abnormal time processing observed in ADHD, some of which could be tested with the application of sequential sampling models. For instance, the executive function deficits hypothesis (e.g., Barkley, 1997b) suggests that impaired time processing is a result of dysfunctional response inhibition and deficits in executive functioning. This would lead to a systematic underestimation of elapsed time intervals that can be observed in perceptual timing tasks. The cognitive energetic theory (e.g., Sergeant, 2000; van der Meere, 2005, 2009) proposes that abnormal time processing results from dysfunctional state regulations (e.g., mismatch between a participant's state of arousal and the stimulation provided by the task). More motivation-based theories (e.g., Sonuga-Barke, 2002; Sonuga-Barke et al., 1998) propose that participants with ADHD possess an internal clock, which runs faster than those of participants without ADHD. This would lead to a delay aversion and to underestimations of particularly long time intervals. An AAM analysis applied to a Duration discrimination task showed that the internal clock of participants with ADHD (children and adults) ran faster than that of participants without ADHD (Shapiro & Huang-Pollock, 2019).

None of the reviewed studies collected neuronal measures during task performance. However, brain imaging studies found that temporal processing is based on the communication in dopamine-rich pathways between frontal and limbic regions (De La Fuente et al., 2013; Konrad & Eickhoff, 2010), which are areas presumed to be associated with ADHD. For instance, dopaminergic stimulants have been shown to improve behavioral performance on time perception tasks (Rubia et al., 2009). Therefore, tasks from this test domain may be particularly suitable for the study of ADHD-specific characteristics.

### Sustained Attention

CPTs were commonly applied in this test domain. Evidence suggested ADHD is characterized by difficulties in maintaining attention. There was also preliminary evidence for differences between ADHD endophenotypes that warrants further study. Reviewing findings for this test domain confronted us with many challenges. First, many studies did not examine changes in performance measures over the course of a task. Instead, they focused on changes in performance measures between conditions with short versus long interstimulus intervals (ISIs). Nevertheless, changes in performance over time may serve as a good proxy for one's ability to maintain attention over an extended period of time. Specifically, if ADHD is characterized by deficits in sustaining attention, one would expect that the performance of participants with ADHD declines more over time as compared with that of participants without ADHD. Second, many studies did not report mean RTs and/or accuracy but reported measures derived from experimental data that were provided by test makers (e.g., Leppma et al., 2018; Moreno-García et al., 2015; Tinius, 2003). This made it impossible for us to determine how the results from these studies relate to the findings from other studies. Third, some studies employed inhibitory control paradigms (e.g., CCPTs which are CPTs with presentations of frequent rather than rare target stimuli) to study Sustained Attention, which produced results that were neither consistent with other results in the domain Sustained Attention, nor were they consistent with other results in the domain Inhibitory Control we showed.

EGDM analyses found that participants with ADHD had larger increases in tau values when ISI increased as compared with participants without ADHD. The cognitive-energetic model (Sergeant, 2005) and the default-mode network model (Sonuga-Barke & Castellanos, 2007) propose that larger increases in tau values (as a result of increased ISI) are due to difficulties of participants with ADHD to remain in an active mode. A meta-analysis with the DDM suggested that children with ADHD had lower drift rates than children without ADHD (Huang-Pollock et al., 2012). However, the meta-analysis with the DDM needs to be updated because it makes an assumption about the starting point of the process that is not supported by recent analyses (Huang-Pollock, Ratcliff, et al., 2017; Ratcliff et al., 2018).

Studies that utilized frequency-based analyses of EEG power bands found that ADHD adults required a higher level of neural activation (as evidenced by attenuated alpha power) to sustain attention toward the end of the task as compared with adults without ADHD. Decreased alpha power in ADHD has been observed across a range of tasks (Klimesch et al., 2007; Loo et al., 2009). For instance, Loo et al. found that a decreased power in alpha band indexes increased cortical effort in adults with ADHD to perform the task. Other studies (Bresnahan et al., 1999; Bresnahan & Barry, 2002) found that ADHD is characterized by increased power in theta band. Further research is needed to determine whether different ADHD subgroups exhibit specific characteristics in different power bands.

### *Inhibitory Control*

CCPTs and Stop-signal tasks were frequently used in this test domain. Results remain mixed whether these tasks are able to discriminate between participants with and without ADHD (Halperin et al., 1992; Klee & Garfinkel, 1983; Koelega, 1995; Rovet & Hepworth, 2001; Shapiro & Garfinkel, 1986; Zahn et al., 1991). In fact, multiple studies that used CCPTs and Stop-signal tasks found that participants with other clinical disorders (e.g., schizophrenia, psychosis) showed deficits similar to those of participants with ADHD (Arabzadeh et al., 2014; Hughes et al., 2012; Lipszyc & Schachar, 2010). Moreover, many of the reviewed studies suggest subtype-specific differences in this test domain. This stands in contrast with other studies that did not find subtype-specific differences (e.g., Edwards et al., 2007; Egeland, & Kowalik-Gran, 2008; Scheres et al., 2001). Reviewing this test domain revealed multiple difficulties in comparing results across studies. First, some studies did not test the hypothesis whether participants with ADHD produce more commission errors than participants without ADHD (in particular without examining the effects of ISI). Instead, they focused on the finding that participants with ADHD showed a large proportion of very slow RTs particularly for long ISI as compared with short ISI—a finding that seems more related to the concept of Sustained Attention. Studying different cognitive concepts with the same type of task makes it difficult to compare results across studies and to disentangle the cognitive aspects that characterize ADHD. Second, evidence remained mixed on whether behavioral measures from the CCPT relate to symptoms assessed with parent or teacher ratings (Epstein et al., 2003). Based on the difficulties in this test domain, it is not surprising that the CCPT showed poor sensitivity to correctly identify participants with ADHD (Epstein et al., 1998; McGee et al., 2000).

Multiple applications of sequential sampling models raised uncertainty about what cognitive concepts CCPTs and Stop-signal tasks measured. For instance, the AAM application by Ratcliff et al. (2018) and the EGDM application by Weigard et al. (2019) suggested that error responses in the CCPT and the Stop-signal task do not solely index failures in inhibitory control processes (also see: Matzke et al., 2019). Rather, behavioral measures were confounded by biases in the decision process (i.e., biases in starting points, which index a participant's preference to rely on prior expectations rather than presented information to reach a decision). To date, researchers debate whether CCPTs and Stop-signal tasks do indeed measure deficits in inhibitory control (Alderson et al., 2007; Barkley, 1997a; Lipszyc & Schachar, 2010; Nigg, 2001; Nikolas et al., 2019). For instance, dysfunctional regulations of arousal, attention, integration of information, or expectations could be the actual underlying cognitive processes that are dysfunctional and that cause deficits in inhibitory control (Milich et al., 1994; Nigg, 2001; Sergeant et al., 1999).

Studies that additionally collected neurophysiological measures during CCPTs and Stop-signal tasks found that participants with ADHD showed significant differences to participants without ADHD in areas involved in error processing. Moreover, multiple studies suggest that the detection of clinical characteristics in neurophysiological measures heavily depend on the specifics of the task (e.g., task difficulty, ISIs, frequency of target stimuli). Ultimately, the characteristics of ADHD remain unclear as studies propose multiple neural components and concepts to find ADHD-specific characteristics in this test domain.

## Suggestions for Improving Cognitive Testing

Reviewing studies across a range of test domains shows one of the biggest challenges that needs to be overcome: designing studies so that they can be directly compared. Currently, problems arise because tasks differ, participant groups differ, and the degree to which data to all these aspects are available differs. Even when multiple studies use the same tasks, details in the procedures of these tasks differ to such a degree that often they cannot be directly compared unambiguously. This means that contradictory results can occur because of differences between participant groups; differences between task specifics (e.g., cue-stimulus interval, presentation time of stimuli, digits presented in singles or triples vs. presented sequentially); and/or differences between tasks. To address this challenge, we might aim for standards that define the requirements on tasks and methods used to characterize mental health disorders such as ADHD. Perhaps one partial solution might be to include some standard conditions across studies so that there is some basis for comparison. Most importantly, we may want to suggest how much and what kind of data needs to be collected and to be made available to allow test results to be compared (e.g., sample characteristics of comorbid diagnoses, raw cognitive data from test providers, not just their commercialized cognitive scores).

The discussion so far also raises questions as to whether commonly used tasks validly assess their target cognitive concept(s). Terms such as *inhibition*, *selective attention*, and *inhibitory control* are useful for talking about the possible locus of deficits. Sometimes one task is assumed to measure several of these concepts, and so it is difficult to relate tasks to concepts. Thus, the concepts are not particularly useful for specifying tests that measure these concepts and within these tests, they do not specify which measures correspond to these concepts (as noted in the Method section: System of Study Classification). It is difficult to see what to replace these concepts with, but we may want to reevaluate the validity and reliability of measures (e.g., scores of cognitive flexibility, indices of sustained attention) provided by commonly used tasks and to be on the watch for more direct relationships between disorders and measures and/or model-based constructs.

We emphasize that the computational modeling applications that were discussed made us question whether the CCPT does indeed measure inhibitory control (see summary of test domain Inhibitory control in previous subsection). Moreover, we showed that sequential sampling models can help to test different cognitive concepts hypothesized to be deficient in ADHD. For instance, multiple studies (Senderecka et al., 2012 for the test domain Inhibitory Control; Merkt et al., 2013 for the test domain Selective Attention) concluded that ADHD is characterized by slowed processing speed (owing to slower mean RTs for participants with ADHD compared with those without ADHD). We illustrated that ADHD-specific slower mean RTs sometimes stemmed from deficits in cognitive processing (e.g., deficits in information integration, perceptual processing), but they also sometimes stemmed from the accommodation of a cautious response strategy. Hence, the findings from a range of cognitive tasks suggests that the notion of ADHD being characterized by slow processing speed seems not to represent a universal characteristic (e.g., Friedman-Hill et al., 2010 for the test domain Cognitive Flexibility; Fosco et al., 2019 for the test domain Inhibitory Control; Mulder et al., 2010 for the test domain Selective Attention).

Cognitive tasks need to be evaluated with respect to their internal and external validity to increase the possibility to measure cognitive characteristics that are generalizable to contexts outside of the laboratory test setting. We argue that cognitive components can be informative beyond cognitive tests, particularly when administering a set of cognitive tests rather than one single test. The utility of cognitive testing is further increased if each test is dedicated to the study of a specific characteristic of ADHD, including cognitive and social aspects. We hypothesize that stronger associations between decisions across contexts could be made when cognitive testing also involves the study of intraindividual differences across multiple conditions of the same test, asking, for instance, questions such as the following: Which components of the decision process change if the frequency of a stimulus type is changed or if the participant is told to focus on being fast rather than accurate? Will the participant use the new information to modify processing? How much will they rely on their a priori expectation? Answers to questions like those presented above may eventually guide the characterization of ADHD endophenotypes.

Evidence from cognitive psychology should have more impact in the design of cognitive tests. For instance, future research may consider the following findings from cognitive psychology when designing task-switch paradigms (Ging-Jehli & Ratcliff, 2020; Madden et al., 2009; Rogers & Monsell, 1995; Rubinstein et al., 2001; Schmitz & Voss, 2012; Schneider & Logan, 2005). First, the longer the CSI, the more likely are participants able to compensate for their deficits in cognitive flexibility. Second, the more related the tasks that compose the task-switch paradigm, the less demanding task switching, unless response congruency (or stimulus congruency) is varied across tasks to produce conflicts between tasks. Moreover, varying interstimulus interval (ISI) could be used to study the concept of sustained attention in a range of tasks.

## Suggestions for Applying Computational Models

Most studies that used summary statistics either focused on accuracy or mean correct RT. The advantage of sequential sampling models is the possibility to consider simultaneously entire RT distribution shapes for correct and error responses (and corresponding accuracy values). These models allow not only for predictions of choice probabilities and mean RTs but also for identification of the sources of behavioral choices (e.g., response bias, perceptual bias, failures in inhibition control). These sources may be more sensitive for distinguishing between clinical and nonclinical participants, between different ADHD subtypes, or between various severities of ADHD symptoms. We emphasize that the interpretation of model parameters depends on the task and interpretations should not be separated from the task in which they are estimated.

Unlike most other analysis methods, applications of sequential sampling models have multiple hurdles to overcome. First, the models have to adequately fit the experimental data (accuracy and correct and error RT distributions) before it can be legitimately used to interpret the experimental data. This means that applications should have plots of fits to data (cf., Ging-Jehli & Ratcliff, 2020; Ratcliff & Childers, 2015) presented in the text, and appendix, or at least a supplement. Second, the models need to be adequately parametrized. This means considering which model parameters to keep constant across conditions based on a priori hypotheses or theories. Keeping constant some of the model parameters yield to a constrained model that is more highly falsifiable than fits to a single condition. Third, correlational analyses between model parameters should be performed to check to what extent model parameters trade-off against each other (and therefore question the degree to which model parameters index distinct components). For instance, Ging-Jehli and Ratcliff (2020) found that nondecision time and drift rate did not correlate with each other and indexed different cognitive components of task-switching. However, this may not be the case for simpler tasks such as CPTs and CCPTs.

Multiple studies found that, although parameters trade off, this effect is much smaller than the individual differences in model parameters (e.g., Ratcliff et al., 2006, 2010, 2011). It has been shown that tradeoffs in parameter values are usually three to five times smaller than individual differences. Because variances add, this produces very small effects (5%) on individual differences. In Ratcliff et al. (2010, 2011), boundary separation, nondecision time, and drift rate parameters correlate 0.4 to 0.6 across tasks and drift rates correlate with IQ in the 0.5 range. These are strong individual differences that are captured in the modeling.

The application of many computational models often requires adjustments of the cognitive test. For instance, to estimate consistent parameters, the task needs to have enough trials. A rule of thumb is a bare minimum of 50 or more trials per condition with several conditions, the more data, the better the parameter estimates (Ratcliff & Childers, 2015;

Ratcliff et al., 2018). This means that the design of a task used for model-based analysis should not be an add-on to a larger battery with say 10 min of testing (it may take 5 min for the participant to be instructed, work out how to perform the task, and settle in to performing the task in a stable manner). The experiment needs to be designed so that the model-based analysis have enough power to allow conclusions to be drawn from it. If the experiment can be designed for modeling, then 500 to 1,000 observations in total should be collected, which may require 30–45 min of testing. However, the number of observations depends on the number of conditions in a task. Moreover, the difficulty level of the task needs to be adjusted so that there is a sufficiently high error rate in some conditions (i.e., rule of thumb: larger than 10% per task, Ratcliff, 2014). Ideally, the task should involve multiple conditions with a range of accuracy rates between 70% and 90%. Estimating model parameters based on a low number of observations or a few error responses can result in biased or inconsistent estimates (or both), and this limits the potential effects that can be detected with model-based analyses. If a task does not produce enough error responses, the benefits of the computational models cannot be fully utilized.

Sequential sampling models should be simultaneously fit to accuracy and RT distributions of correct and error responses for all conditions. This will lead to a highly constrained model, one that will be falsifiable in many cases (see also: Van Zandt et al., 2000). We suggest checking goodness of fit not only with the use of critical values such as G-square or chi-square values. Rather, deriving model predictions and plotting those predictions against data for accuracy and different quantile RTs (e.g., .1, .5, and .9 quantile RTs) for each condition and for each participant, will transparently show how well the model fits the data (e.g., Ging-Jehli & Ratcliff, 2020).

Computational models sometimes also require adjustments in their specifications. For instance, previous DDM analyses of Flanker tasks showed that the standard DDM does not apply and that modifications are needed. Such models include the spotlight model (White et al., 2011), the dual stage model (Hübner et al., 2010), or the race diffusion model (Tillman et al., 2020).

Studies (Ratcliff et al., 1999; Smith & Ratcliff, 2015) have shown that the introduction of variability parameters (i.e., variabilities in nondecision time component, starting points, or across-trial variability in drift rates) allow for accounting specific accuracy-response time patterns (i.e., faster error responses than correct responses as a result of variation in starting points). However, research has shown that such variability parameters are difficult to recover (Ratcliff & Tuerlinckx, 2002) without sufficient numbers of observations. Therefore, group-specific analyses in variability parameters are less robust than group-specific analyses in main model parameters.

## Suggestions for Integrating Neural Measures

Multiple limitations occur when examining results from neurophysiological measures. For example, a single EEG-ERP component (e.g., P3) has been associated with many different cognitive processes. Therefore, finding differences in a single component might not map into the construct being examined. Furthermore, because of the large number of EEG-ERP components that can be examined, it seems tempting to focus on significant results and report those results with post hoc explanation of why that particular component (which might be amplitude, frequency band, or onset time) relates to the process or participant difference being studied. The problem is that the collection of EEG measures without a theoretical foundation biases the investigator to focus on significant results only. A remedy to this problem is the use of single-trial measures integrated into model-based analyses (Ratcliff et al., 2016) or other joint modeling approaches discussed earlier (see also: Turner et al., 2017).

Most of the studies focused on latency and peak amplitude when characterizing EEG-ERPs. However, studies have shown that it can be beneficial to measure the onset or offset of a component rather than the peak. Other measures such as the fractional area latency are particularly suitable for making comparisons with RTs (e.g., Luck, 2014; Zoumpoulaki et al., 2015).

Another limitation occurs in the use of activity-based measures and neural theories based on resting state analyses. These theories do not allow deriving testable, quantitative predictions because they do not map into behavioral measures in any agreed-upon way. Therefore, in the worst case, these theories might be able to explain any possible pattern of results, making them unfalsifiable. A long-term aim of theory is to form a consistent picture of the different theories, find specific ways of relating these neurophysiological measures and analyses to behavior and individuals, and provide testable predictions.

Different ADHD phenotypes may have deficits that affect their decision process at different time points. For instance, participants with ADHD who start their decision process late (attributable to a slow perceptual encoding phase or a slow accessibility to stored memory, henceforth "late starter") may show pronounced hypoactivation in brain areas associated with the default-mode network. In this case, the neural activity would be associated with the nondecision time component of the DDM. In contrast, participants with ADHD who tend to have lapses of attention (attributable to an abnormal propensity for daydreaming, henceforth "daydreamer") may also show pronounced hypoactivation in brain areas associated with the default-mode network similar to late starters. The neural activity in this case would be associated with the drift rate because the onset of the decision process is not what is deficient. Rather, a daydreamer may lose their train of thought *during* the decision process, leading to poorer information integration. Hence, both prospective ADHD endophenotypes (i.e., a late starter, daydreamer) may exhibit the same neural activity (i.e., hypoactivation in the default-mode network). However, the time dynamics of the neural pattern become quantifiable and psychologically interpretable with the conjoint application of computational modeling and neurophysiological measures such as electroencephalography (EEG).

## Suggestions for Integrating Sample Characteristics

Synthesizing findings across the different test domains indicate a high heterogeneity in test performance among participants with ADHD. Many studies centered their investigation around specific ADHD groups (e.g., boys aged between 7 and 14 years and diagnosed with ADHD-C or ADHD-H). However, summarizing the findings across test domains illustrated the importance to account for subgroup-specific differences in ADHD. For instance, a subgroup of ADHD (i.e., individuals with ADHD-I) seems to be more sensitive to perceptual noise than another subgroup of ADHD (i.e., individuals with ADHD-C; see section on the test domain: Cognitive Flexibility). Other studies also found subtype-specific differences in neurophysiological measures (Clarke et al., 2001; Fair et al., 2013; Loo et al., 2003). For instance, Fair et al. (2013) found ADHD-C to be characterized by atypical connectivity in the insular cortex, as well as in the midline default network components, whereas ADHD-I to be characterized by atypical connectivity in the cerebellum and in the dorsolateral prefrontal cortex.

Studies that accounted for subtype differences in their primary analysis often used different criteria for subclassifying participants with ADHD (Epstein et al., 2011; Pritchard et al., 2008; Solanto et al., 2009). This can make comparisons across studies difficult. For instance, the study by Carr et al. (2010) assigned participants with ADHD-I, but with teacher' and parents' ratings of hyperactivity and restlessness below the mean to a group referred to as "ADD." It sometimes remained unclear to what extent the different results are attributable to differences in the subclassification of participants with ADHD or to differences in the task specifics.

Future studies should consider which cognitive characteristics best distinguish ADHD from frequently co-occurring comorbid diagnoses such as autism spectrum disorder (ASD). For instance, the studies we reviewed that used the Navon task or the Attentional blink task suggested that individuals with ADHD-I are characterized by a detail-oriented, local processing mode (Fink et al., 1996; Song & Hakoda, 2012; Yeo et al., 2003). On the other hand, ASD is defined by restricted and repetitive behavior which also includes a detail-oriented processing mode, among other modes (APA, 2013; Levy et al., 2009). This raises the question as to where to place individuals with ADHD-I on the broad spectrum of ASD. To date, it is unclear what the determining difference is between individuals with ADHD-I, high-functioning ASD, or both. In contrast, an ADHD group characterized by high severity of hyperactivity and distractibility may accommodate a more global-oriented processing mode. For that ADHD group it may be that the level of processing mode (local vs. global) is what distinguishes them from ADHD-I and/or ASD. To account for the heterogeneity in ADHD, a set of multiple cognitive tasks seems most promising.

## Conclusion

Sequential sampling models are promising tools to characterize ADHD endophenotypes. However, it will be necessary for the field to show that the results of modeling provide insights beyond those provided by purely experimental approaches. Further research is needed to show that a set of sequential sampling model parameters (e.g., drift rates, nondecision time components) can serve as an endophenotype, allowing identification of homogenous subtypes of ADHD.

We focused on three frequently applied computational models (DDM, AAM, EGDM) across six test domains of clinical cognitive testing. There are other test domains that we did not discuss, such as reinforcement learning, for which also other computational models have been used. Moreover, our qualitative meta-analysis focused on studies that investigated differences between participants with and without ADHD, or between participants with different ADHD endophenotypes. However, for the design of effective treatments for different ADHD endophenotypes (i.e., drug interventions, cognitive–behavioral therapies), it will also be important to understand how such clinical interventions affect different cognitive components (e.g., treatment interventions that used computational models).

Our review is specific to (neuro)cognitive testing for ADHD. However, many issues that we have raised (see the summary in Table 10) generalize to neuropsychological testing and model-based approaches in psychiatry. For instance, studies dedicated to measure a single construct (e.g., deficits in working memory) differ in many ways (e.g., the task used, task manipulations, participant groups) so that they cannot be directly compared. Perhaps some standard conditions could be included to allow comparisons across tasks. Another issue concerns the extent to which tasks indeed measure targeted cognitive concepts such as *inhibition failures* or *processing speed*. Importantly, there are usually no hypotheses about how processing in a task connects to the concept being measured. For example, there is no one to one correspondence between tasks and concepts because a single task is often used to measure different cognitive concepts. This is also a problem for neurophysiological analyses. For instance, rarely are theoretical, quantifiable reasons (beyond a simple verbal plausibility argument) provided that explain why cognitive concepts such as sustained attention could be indexed by measures such as a frequency band or an ERP component.

Ultimately, even computational modeling, as it is currently used, has limitations. To use these models (i.e., interpret their results), they need to fit the data. This is even more important considering that for some tasks (e.g., conflict tasks), standard models have been shown to fail and new models have been developed (so applications of standard models are invalid). Moreover, enough data have to be collected in a task to allow measurement of the processing components (parameters) to the degree needed for the analysis. These criticisms suggest significant weaknesses in the neuropsychological approach to clinical issues. However, we view these weaknesses as opportunities that will spur new high-quality research that will advance the field.

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(*Appendix follows*)

# Appendix

## Task Descriptions, Sample Characteristics, and Results of the Reviewed Studies

**Table A1**
*Description of Task Paradigms Covered in This Study*

| Authors | Test domain | Task description |
|---|---|---|
| Hung et al. (2016) | Cognitive flexibility | Participants were presented with one-digit numbers (1 to 9). If a solid rectangle surrounded the number, participants had to indicate (with keypresses) whether the number was smaller or larger than 5 (task A). If a dashed square surrounded the number, participants had to indicate whether the number was odd or even (task B). The paradigm consisted of two types of blocks, namely pure blocks and mixed blocks. In the pure blocks, participants performed either task A or task B repeatedly (i.e., pure trials). In the mixed blocks, participants switched between task A and B every third trial (i.e., no-switch trials and switch trials). Task switches occurred predictable every third trial. |
| Cepeda et al. (2000) | Cognitive flexibility | The paradigm involved two tasks and three blocks. On each trial, participants were presented with one of two numbers (a "1" or a "3"), displayed either singly or in triples. The two tasks only differed in the cue that instructed participants to respond: "what number?" or "how many?" In the first and second blocks, the cue (either "what number?" or "how many?") remained constant (e.g., a single task). In the third block, the cue changed predictably every third trial. In this third block, the stimuli and cues were combined such that responses were either congruent in both tasks (i.e., congruent trials), or incongruent in one of the tasks (i.e., incongruent trials). Congruent trials involved number-cue combinations such as "1" — "What number?"; and "333" — "How many?." Incongruent trials involved number-cue combinations such as "111" — "What number?"; and "3" — "How many?." The response-stimulus interval (RSI) was between 300ms and 600ms for all blocks. |
| Oades and Christiansen (2008) | Cognitive flexibility | The paradigm was the same as conducted by Cepeda et al. (2000) with the following modifications: First, the cue was presented first, followed by the stimulus (i.e., CSI varied between 100ms and 1200ms on a trial-by-trial basis) instead of presenting cue and stimulus simultaneously as in Cepeda et al. (2000). In addition, task-switches occurred randomly (every three to seven trials) instead of predictably every third trial as in Cepeda et al. (2000). |
| Luna-Rodriguez et al. (2018) | Cognitive flexibility | The paradigm consisted of congruent and incongruent trials. On congruent trials, the large letter (number) was the same as the smaller letters (numbers). On incongruent trials, the large letter (number) was not the same as the smaller letters (numbers). In this paradigm, each trial started with a blank screen for 500ms, followed by the cue (presented for 200ms), and the stimulus (presented for 200ms). |
| Song and Hakoda (2012) | Cognitive flexibility | First experiment: participants were presented a large digit, composed of incongruent smaller digits. In the "global condition," participants had to indicate whether the large digit was a target digit (i.e., 3, 6) or a nontarget digit (i.e., 2, 5, 8, 9) by pressing one of two keys. In the "local — condition," participants had to indicate whether the smaller digits were target or nontarget digits. Song and Hakoda (2012) administered this task with paper and pencil such that participants had approximately 2,600ms to encode each stimulus (because there were 30 stimuli per sheet and participants were given 80 s for each sheet). Second experiment: the first experiment was expanded to four conditions and three stimuli types as follows: Type 1 stimuli were digits (i.e., 2, 3, 5, 6, 8, 9) composed of dots (i.e., no-conflict stimuli). Type 2 stimuli were rectangles composed of small numbers (i.e., 2, 3, 5, 6, 8, 9). Type 3 stimuli were digits (i.e., 2, 3, 5, 6, 8, 9) composed of incongruent, smaller digits (i.e., conflict stimuli). The "global" condition involved stimuli from types 1 and 3. Researcher's hypothesis: if the local features interfere with processing the global feature, then performance for type 3 stimuli would be worse than for type 1 stimuli. The "local" condition involved stimuli from types 2 and 3. Researcher's hypothesis: if the global feature interferes with processing the local features, then performance for type 3 stimuli would be worse than for type 2 stimuli. |

(*Appendix continues*)

**Table A1** (*continued*)

| Authors | Test domain | Task description |
|---|---|---|
| Carr et al. (2010) | Cognitive flexibility | In the Attentional blink task, participants were presented with a stream of 22 letters (each appearing for 90 ms without any additional interstimulus interval). There were in total 80 streams of letters. The position of the target letter in the stream was unpredictable but always occurred before the probe letter. In the Antisaccade task, each trial began with a central fixation point, followed by a start box superimposing the central fixation point to indicate the beginning of the trial. Afterwards, a target box was presented either to the left or the right of the screen center. The onset of the target box varied randomly between 500 ms to 1,000 ms on a trial-by-trial basis. |
| Metin et al. (2013) | Cognitive flexibility | Antisaccade task (composed of two-choice perceptual task [2-CRT] and conflict control test [CCT]).In the 2-CRT, participants indicated whether a gray arrow at the screen center was left- or right-pointed with responses made on right or left keys. In the CCT, participants were also presented with a left- or right-pointed arrow, but if the arrow was gray-colored, they indicated the direction of the arrow (congruent trials), and if the arrow was red-colored, they indicated the opposite direction of the arrow (incongruent trials). |
| Friedman-Hill et al. (2010) | Selective attention | In a Perceptual Discrimination task, they manipulated the difficulty level of discrimination (low, medium, high), and the saliency of distractors (low, medium, high). Target images for this task were faces that were created by morphing the image of a primate's face and a woman's face. Participants were asked whether presented target images showed the original primate's face or a morphed image. In the "low distraction" condition, target images were surrounded by unrelated images (i.e., distractors) with lower resolution. In the "high distraction" condition, target images were surrounded by unrelated images with the same resolution as the target. In the "medium distraction" condition, the distractor images were presented with a medium level of distractor salience and a medium level of spatial configuration relative to target images. |
| Schneidt et al. (2018) | Selective attention | Participants had to respond whether a rectangle was oriented horizontally or vertically. The level of task difficulty was manipulated by making the rectangle more or less like a square. Irrelevant, emotionally arousing images (displayed in the background during the task performance) served as distractors. |
| Mulder et al. (2010) | Selective attention | Participants had to indicate the direction of randomly moving dots with keypresses. The level of task difficulty (low vs. high) varied on a trial-by-trial basis, while the type of instructions (speed vs. accuracy) varied on a session-by-session basis. |
| Gohil et al. (2017) | Selective attention | Preceding (presented for 30 ms at the beginning of each trial) distractors (right- or left-pointed arrows) served as subliminal masked cues (e.g., primes). The task was therefore comprised of trials that were either preceded with correct (C) or incorrect (I) primes; and which contained either congruent (C) or incongruent (I) flankers. This resulted in four conditions, namely CC, IC, CI and II (with the first letter referring to prime type, and the second to flanker type). The incorrect primes served to induce additional conflict on trials with incongruent distractors. Comparing CC with IC conditions or CI with II conditions provided one conflict effect (either incompatible or incongruent) on performance. In contrast, comparing CC with II conditions illustrated the effect of two different kinds of conflict (incompatible and incongruent) on performance. |
| Merkt et al. (2013) | Selective attention | The task was composed of two blocks (i.e., rare conflict vs. frequent conflict). Participants were presented with a three-digit number and asked to indicate whether the middle digit was even or odd with keypresses. The two digits, one on either side of the middle digit, had either the same parity (e.g., 646; congruent trial) or a different parity (e.g., 343; incongruent trial). The "rare conflict" block was composed of 20% incongruent trials, whereas the "frequent conflict" block was comprised of 80% incongruent trials. |
| Weigard and Huang-Pollock (2014) | Selective attention | Participants were presented with a target letter "T" (rotated 90 degrees to the right or left), accompanied by letters "L" that served as distractors. Participants had to locate the target letter on the computer screen and indicate its direction (right- or leftward pointed) with keypresses. On RC-trials: the target letter and the distractors repeatedly occurred in the same locations. On NC-trials: the target letter and the distractors occurred in random, new locations. Researcher's hypothesis: participants would learn where to find the target letter for RC-trials. This would lead to a shorter detection time for RC-trials as compared with NC-trials. These learning effects were examined with a diffusion model analysis; the total number of trials (480 trials) was divided into three epochs, and model parameters estimated for each epoch separately. |

(*Appendix continues*)

**Table A1** (*continued*)

| Authors | Test domain | Task description |
|---|---|---|
| Lenartowicz et al. (2014) | Working Memory | Participants were presented with sequentially illuminating dots for 2 s (encoding phase), followed by a fixation cross displayed for 2 s (maintenance phase). In the subsequent probe phase, another dot was presented for 3 s. Participants had to indicate whether the location of that dot (in the probe phase) matched the location of any of the dots presented during the encoding phase. The level of task difficulty was manipulated by the number of dots presented during the encoding phase. In the "low-demand" condition, either one or three dots were presented. In the "high-demand" condition, either five or seven dots were presented. |
| Weigard and Huang-Pollock (2017) | Working memory | The paradigm was composed of two tasks, namely the digit span task and the numerosity task. A trial started with the digit span task for 1,800 ms. Children had to memorize the order of squares (on a 4 × 4-grid) that were randomly turned red (encoding phase). The number of squares to be remembered varied from two to nine on a trial basis. Following the squares presentation but before recollection, children completed a two-choice numerosity task to prevent active rehearsal (maintenance phase). In this task, children indicated with keypresses whether the number of asterisks displayed in a box was high or low. Subsequently, they had to recollect the order and position of the illuminated squares (probe phase). |
| Valko et al. (2010) | Time perception | For the time reproduction task: Participants watched an animation of a beacon from a lighthouse that lasted between one and eight seconds. Participants were then presented a second beacon for which they had to guess the time interval of the first by pressing a button once the time had elapsed. For the time differentiation task: participants were shown two consecutive stimuli that differed in their presentation duration. They were then asked to indicate which stimulus lasted longer. |
| Baytunca et al. (2018) | Sustained attention | The Stroop task involved two parts: In the first part, participants had to press a key if the word matched the color of the word (i.e., congruent trials), but to withhold pressing any key if the word did not match the color of the word (i.e., incongruent trials). In the second part, participants had to press a key for incongruent trials, but to withhold pressing any key for congruent trials. The responses on the congruent and incongruent trials were collapsed for the analysis. |
| Wiersema et al. (2006) | Inhibitory control | Children were presented with a letter randomly displayed at one of four locations on the screen for 300 ms. They had to press a key whenever the letter "K" was presented (75% of the trials), but to withhold any keypresses whenever another letter than "K" was presented. ISI was either 1,700 ms referred to as "fast blocks" or 2,300 ms referred to as "slow blocks" |
| Lee et al. (2015) | Inhibitory control | The task was composed of blocks with constant interstimulus interval (ISI) and blocks with jittered ISI (Lee et al. call randomization of different ISIs ranging from 1,000 ms to 2,000 ms within a block "jitter"). For the blocks with constant ISI, Lee et al. (2015) reported that the cue-stimulus interval was 1,500 ms and the presentation time of the cues was 300 ms. |
| Huang-Pollock, Ratcliff, et al. (2017) | Inhibitory control | In this CCPT, interstimulus interval (ISI) and the level of difficulty was manipulated. Children were presented with a box containing either a few stars or many stars. They had to press a key whenever the box contained a lot of stars (go trials), but to withhold any keypresses whenever the box contained a few stars (no-go trials). Children were initially randomly assigned to either the "slow event rate" condition (i.e., long ISI) or the "fast event rate" condition (i.e., fast ISI). |
| Kingery (2017) | Inhibitory control | In this CCPT, participants were presented with either high-pitched sounds (i.e., go trials with 2,000 Hz) or low-pitched sounds (no-go trials with 1,000 Hz). |
| Fosco et al. (2018) | Inhibitory control | For a description of the classic version of the Stop-signal task (Table 2). The modified version of the Stop-signal task (i.e., NSSCRTT) was a 2-choice task without any stop-signals. Therefore, the NSSCRTT was identical to the CSST, except that all trials contained go stimuli without any stop-signals. An auditory tone (i.e., stop-signal) was introduced randomly on 25% of the trials. As in most Stop-signal tasks, the latency between the stop-signal and the onset of the go stimulus was dynamically adjusted throughout the task. |
| Tye et al. (2016) | Inhibitory control | Participants were presented with four empty circles. One of those circles was filled either after one second (fast condition) or eight seconds (slow condition). Participants were instructed to press the response key associated with the filled circle as fast as possible. They were additionally informed that they would earn a small reward in the fast condition. |

(*Appendix continues*)

**Table A2**

*Summary of the Results and Sample Characteristics of Studies in the Test Domain: Cognitive Flexibility*

| Authors | Sample characteristics | Results |
|---|---|---|
| Hung et al. (2016) | *ADHD group:*<br>20 boys aged between 8 and 12, $M$ = 10.24 years ($SD$ = 1.78).<br>75% were diagnosed with ADHD-C, 5% with ADHD-H, and 20% with ADHD-I. Diagnoses were based on the Chinese version of the ADHD test developed by Gilliam (1995).<br>*Control group:*<br>20 matched control boys, aged between 8 and 12, $M$ = 10.20 years, ($SD$ = 1.09). | Accuracies and mean RTs (switch, nonswitch, pure trials):<br>*Pure trials:*<br>• ADHD group: 85.6%, 886 ms<br>• Control group: 92.1%, 691 ms<br>*nonswitch trials:*<br>• ADHD group: 70.2%, 1,255 ms<br>• Control group: 86.9%, 1,066 ms<br>*switch trials:*<br>• ADHD group: 69.1%, 1,325 ms<br>• Control group: 86.3%, 1,164 ms<br>*Global switch costs (difference between nonswitch and pure trials):*<br>• ADHD group: −15.4%, +369 ms<br>• Control group: −5.3%, +375 ms<br>*Local switch costs (difference between switch and nonswitch trials):*<br>• ADHD group: −1.1%, +70 ms<br>Control group: −0.6%, +98 ms |
| Cepeda et al. (2000) | *ADHD group:*<br>16 children (62.5% male), aged between 6 and 12, $M$ = 8.9 years, ($SD$ = 1.1). 81% were diagnosed (based on *DSM–IV*) with ADHD-C, and 19% were diagnosed with ADHD-H.<br>*Control group:*<br>16 age- and IQ-matched children (38% male), aged between 6 and 12, $M$ = 8.8 years ($SD$ = 1.4). | Error rates and mean RTs (switch, nonswitch, single trials):<br>*For response compatible trials (i.e., congruent trials):*<br>ADHD group:<br>• single trials: 0.0%; no-switch trials: 4.3%; switch trials: 3.7%<br>• single trials: 885 ms; no-switch trials: 1,763ms; switch trials: 1,967ms<br>Control group:<br>• single trials: 0.0%; no-switch trials: 3.6%; switch trials: 2.5%<br>• single trials: 727 ms; no-switch trials: 1,532 ms; switch trials: 1,675 ms<br>*For response incompatible trials (i.e., incongruent trials):*<br>ADHD group: • single trials: 0.0%; no-switch trials: 17.6%; switch trials: 18.7%<br>• single trials: 915 ms; no-switch trials: 1,775ms; switch trials: 2,470 ms<br>Control group:<br>• single trials: 0.0%; no-switch trials: 15.8%; switch trials:14.1%<br>single trials: 803 ms; no-switch trials: 1,726ms; switch trials: 1,917 ms |
| Oades and Christiansen (2008) | *ADHD group:*<br>57 children (84% male), aged between 6 and 16, $M$ = 10.9 years ($SD$ = 2.7), all children were diagnosed with ADHD-C (based on *DSM–IV*).<br>*Sibling group:*<br>44 phenotypically unselected (e.g., ADHD-unaffected) siblings (48% male), aged between 5 and 18, $M$ = 11.3 years ($SD$ = 3.6).<br>*Control group:*<br>71 independent control children (68% male), aged between 6 and 17, $M$ = 11.0 years ($SD$ = 2.4). | Mean RTs and coefficient of Variation (CV, in ms):<br>*Condition: Cue (Which number?), Stimulus (Incongruent: 111)*<br>• ADHD group: 1,546 ms (CV: 0.69)<br>• Sibling group: 1,616 ms (CV: 0.61)<br>• Control group: 1,565 ms (CV: 0.64)<br>*Condition: Cue (Which number?), Stimulus (Congruent: 1)*<br>• ADHD group: 1,260 ms (CV: 0.72)<br>• Sibling group: 1,252 ms (CV: 0.67)<br>• Control group: 1,283 ms (CV: 0.67)<br>*Condition: Cue (How many?), Stimulus (Incongruent: 3)*<br>• ADHD group: 1,217 ms (CV: 0.60)<br>• Sibling group: 1,510 ms (CV: 0.55)<br>• Control group: 1,446 ms (CV: 0.55)<br>*Condition: Cue (How many?), Stimulus (Congruent: 333)*<br>• ADHD group: 1,364 ms (CV: 0.71)<br>• Sibling group: 1,550 ms (CV: 0.70)<br>• Control group: 1,344 ms (CV: 0.66)<br>Note: Coefficient of Variation is calculated as follows: RT standard deviation/mean RTs. |

(*Appendix continues*)

**Table A2** (*continued*)

| Authors | Sample characteristics | Results |
|---|---|---|
| Luna-Rodriguez et al. (2018) | *ADHD group:*<br>38 adults, 55.3% male, $M_{age}$ = 36.14 years ($SD$ = 12.71). No information on *DSM–IV* subtypes.<br>*Control group:*<br>39 adults, 51.3% male, $M_{age}$ = 33.61 years ($SD$ = 9.81). | Mean RTs and error rates across conditions:<br>(approximations from the figures)<br>*Condition 1: Constant levels of attentional set, and task repetition*<br>• ADHD group: 5.0%, 750 ms<br>• Control group: 4.0%, 700 ms<br>*Condition 2: Mixed levels of attentional set, and task repetition*<br>• ADHD group: 6.0%, 950 ms<br>• Control group: 5.0%, 850 ms<br>*Condition 3: Constant levels of attentional set, and task switch*<br>• ADHD group: 5.0%, 820 ms<br>• Control group: 6.0%, 750 ms<br>*Condition 4: Mixed levels of attentional set, and task switch*<br>• ADHD group: 10.0%, 1,150 ms<br>Control group: 9.0%, 990 ms |
| Song and Hakoda (2012) | *ADHD group:*<br>15 children aged between 8 and 13, $M$ = 11 years ($SD$ = 1.47), 73% male. All children were diagnosed with *DSM–IV* subtype ADHD-I.<br>*Control group:*<br>19 age- and gender matched children, $M_{age}$ = 11 years ($SD$ = 1.54), 74% males. | First version (dependent variable: accuracy):<br>*"Local" - condition:*<br>• ADHD group: 80.0%, Control group: 80.0%<br>*"Global" - condition:*<br>• ADHD group: 60.0%, Control group: 80.0%<br>Second version (dependent variable: mean RTs):<br>*"Global, control" - condition:*<br>• ADHD group: 820 ms, Control group: 620 ms<br>*"Global, treatment" - condition:*<br>• ADHD group: 1,150 ms, Control group: 780 ms<br>*"Local, control" - condition:*<br>• ADHD group: 1,000 ms, Control group: 600 ms<br>*"Local, treatment" - condition:*<br>ADHD group: 1,030 ms, Control group: 780 ms |
| Baytunca et al. (2018) | *ADHD group:*<br>41 children, 85.4% male, $M_{age}$ = 10.88 years ($SD$ = 1.96). *DSM–IV* subtype diagnoses: $N_{ADHD-I}$: 24, $N_{ADHD-C}$: 17.<br>*ADHD + SCT group:*<br>42 children, 54.8% male, $M_{age}$= 9 years ($SD$ = 1.18). *DSM–IV* subtype diagnoses: $N_{ADHD-I}$: 24, $N_{ADHD-C}$: 18.<br>Subjects needed to have a minimum of 4 SCT symptoms rated by parents and teachers, respectively. There were significantly more females in this group than in the other groups ($p < .05$).<br>*Control group:*<br>24 children, 75% male, $M_{age}$ = 10.88 years ($SD$ = 1.36). | Error rates, mean RTs for correct responses:<br>• ADHD group: 50.0%, 1,221 ms<br>• ADHD + SCT group: 42.0%, 1,214 ms<br>Control group: 19.0%, 1,256 ms |
| Carr et al. (2010) | *ADHD group:*<br>86 children aged between 13 and 17. *DSM–IV* subtype diagnoses. Sample characteristics by subtype:<br>ADHD-C: $N$ = 37, 76% male, $M_{age}$ = 15 years ($SD$ = 1.1). Comorbidities included: 13 subjects with Oppositional Defiant Disorder (ODD), 2 subjects with Conduct Disorder (CD), 1 subject with Anxiety Disorder.<br>ADHD-I:<br>$N$ = 34, 62% male, $M_{age}$ = 15.3 years ($SD$ = 1.2). Comorbidities included: 3 subjects with ODD. | Attentional Blink task:<br>Probe detection accuracies across conditions:<br>(approximation from the figures)<br>*Control group:*<br>• single task: lag(1) = 90.0%, lag(3) = 90.0%, lag(5) = 90.0%<br>• dual task: lag(1) = 68.0%, lag(3) = 52.0%, lag(5) = 60.0%<br>*ADHD-C group:*<br>• single task: lag(1) = 90.0%, lag(3) = 90.0%, lag(5) = 90.0%<br>• dual task: lag(1) = 60.0%, lag(3) = 54.0%, lag(5) = 50.0%<br>*ADD group:*<br>• single task: lag(1) = 90.0%, lag(3) = 90.0%, lag(5) = 90.0%<br>• dual task: lag(1) = 71.0%, lag(3) = 70.0%, lag(5) = 71.0% |

(*Appendix continues*)

**Table A2** (*continued*)

| Authors | Sample characteristics | Results |
|---|---|---|
| | ADD group:<br>post hoc sub-selection of subjects diagnosed with ADHD-I and ratings of hyperactivity/restlessness below the mean score (based on Conners' teacher's and parents' ratings). $N$ = 15, 47% male, $M_{age}$ = 15.1 years ($SD$ = 1.1).<br>*Control group:*<br>71 children aged between 13 and 17, $M$ = 15.5 years ($SD$ = 1.0), 54.1% male, 1 subject with diagnosis of ODD. | Antisaccade task:<br>Directional error rates and mean RTs across conditions: (approximation from the figures)<br>*Prosaccade condition:*<br>• Control group: 0.0%, 200 ms<br>• ADHD-C group: 0.1%, 210 ms<br>• ADD group: 0.0%, 200 ms<br>*Antisaccade condition:*<br>• Control group: 0.1%, 275 ms<br>• ADHD-C group: 0.3%, 290 ms<br>ADD group: 0.2%, 310 ms |
| O'Driscoll et al. (2005) | *ADHD group:*<br>22 boys aged between 11 and 14. Subtype diagnosis based on *DSM–IV*: ADHD-C: $N$ = 10, $M_{age}$= 12.38 years ($SD$ = .57). 1 boy with comorbid Anxiety Disorder.<br>ADHD-I: $N$ = 12, $M_{age}$ = 12.74 years ($SD$ = .60). 1 boy with comorbid Anxiety Disorder.<br>*Control group:*<br>10 boys, aged between 11 and 14, $M_{age}$ = 12.66 years ($SD$ = .58). | Error rates:<br>*Control group:*<br>• no-switch trials: 7.0%<br>• switch trials: 11.0%<br>*ADHD-I group:*<br>• no-switch trials: 12.0%<br>• switch trials: 16.0%<br>*ADHD-C group:*<br>• no-switch trials: 13.0%<br>switch trials: 20.0% |
| Metin et al. (2013) | *ADHD group:*<br>70 children (86% male), aged between 6 and 17 ($M$ = 12.1 years, $SD$ = 2.3). All children were diagnosed with ADHD-C based on *DSM–IV*. The ADHD group had a significantly lower IQ than the control group ($p < .05$).<br>*Control group:*<br>50 children (66% male), aged between 6 and 17 ($M$ = 12.2 years, $SD$ = 2.3). | Two-Choice Perceptual Discrimination Task (2-CRT). Conflict Control Task (CCT; similar to the 2-CRT but with additional incongruent trials).<br>Change in performance from 2-CRT to CCT (congruent trials):<br>*ADHD group:*<br>• Error rate decreased by 5.0%<br>• Mean RTs increased by 99 ms<br>• Drift rate decreased from 1.96 to 1.74<br>• Nondecision time (in sec) increased from 0.2 to 0.25<br>*Control group:*<br>• Error rate decreased by 5.0%<br>• Mean RTs increased by 107 ms<br>• Drift rate decreased from 3.28 to 2.77<br>• Nondecision time (in sec) increased from 0.25 to 0.31<br>Change in performance from 2-CRT to CCT (incongruent trials):<br>*ADHD group:*<br>• Error rate increased by 11.0%<br>• Mean RTs increased by 205 ms<br>• Drift rate decreased from 1.96 to 1.09<br>• Nondecision time (in sec) increased from 0.2 to 0.32<br>*Control group:*<br>• Error rate increased by 8.0%<br>• Mean RTs increased by 232 ms<br>• Drift rate decreased from 3.28 to 2.28<br>• Nondecision time (in sec) increased from 0.25 to 0.42<br>Change in parameters from 2-CRT to CCT (all trials):<br>*ADHD group:*<br>• Boundary separation increased from 0.92 to 1.06<br>*Control group:*<br>• Boundary separation increased from 0.89 to 1.05<br>Note: Fast-dm software (Voss & Voss, 2007) was used to estimate the diffusion model parameters. |

(*Appendix continues*)

**Table A2** (*continued*)

| Authors | Sample characteristics | Results |
|---|---|---|
| Salum et al. (2014) | Classification of children (aged between 6 and 12) into groups based on severity of inattention (groups a) and hyperactivity (groups b) (Development and Well-Being Assessment Scale):<br>1) clinical ADHD groups:<br>*Group 1.a:* ADHD diagnoses (based on *DSM–IV*).<br>Sample characteristics: $N$ = 53 ($N_{\text{ADHD-I}}$ = 36, $N_{\text{ADHD-C}}$ = 17), $M_{\text{age}}$ = 9.5 years ($SD$ = 1.8), 57% males.<br>*Group 1.b:* ADHD diagnoses (based on *DSM–IV*).<br>Sample characteristics: $N$ = 32 ($N_{\text{ADHD-C}}$ = 15, $N_{\text{ADHD-H}}$ = 17), $M_{\text{age}}$ = 9.8 years ($SD$ = 1.9), 53% males.<br>2) subthreshold moderate groups:<br>*Group 2.a:* inattentive score between 6 and 11, and a maximum of five full ADHD symptoms.<br>Sample characteristics: $N$ = 312, $M_{\text{age}}$= 9.9 years ($SD$ = 2.0), 53% male.<br>*Group 2.b:* hyperactive/impulsive score between 6 and 11, and a maximum of five full ADHD symptoms.<br>Sample characteristics: $N$ = 225, $M_{\text{age}}$= 9.4 years ($SD$ = 1.9), 56% males.<br>3) subthreshold minimal groups:<br>*Group 3.a:* inattentive score between 1 and 5, and a maximum of two full ADHD symptoms.<br>Sample characteristics: $N$ = 590, $M_{\text{age}}$= 9.9 years ($SD$ = 2.0), 51% males.<br>*Group 3.b:* hyperactive/impulsive score between 1 and 5, and a maximum of two full ADHD symptoms. Sample characteristics: $N$ = 658, $M_{\text{age}}$= 9.9 years ($SD$ = 2.0), 50% males.<br>4) asymptomatic groups:<br>*Group 4.a:* inattentive score of 0.<br>Sample characteristics: $N$ = 229, $M_{\text{age}}$= 9.7 years ($SD$ = 2.0), 45% males.<br>*Group 4.b:* hyperactive/impulsive score of 0. Sample characteristics: $N$ = 227, $M_{\text{age}}$ = 9.9 years ($SD$ = 2.1), 46% males.<br>Subjects (of any group) were excluded if they received any psychiatric medication and/or had co-morbid Conduct Disorder, Oppositional Defiant Disorder, Anxiety Disorder, Depressive Disorder, Mania, Psychoses, Pervasive Developmental Disorder, Tics, Eating Disorders | Two-Choice Perceptual Discrimination Task (2-CRT). Conflict Control Task (CCT; similar to the 2-CRT but with additional incongruent trials).<br>2-CRT (%correct, %outlier, mean RTs, RT standard deviation):<br>• Group 1.a: 71.4%, 4.3%, 504 ms, 228 ms<br>• Group 1.b: 69.7%, 4.2%, 503 ms, 231 ms<br>• Group 2.a: 77.7%, 2.8%, 501 ms, 188 ms<br>• Group 2.b: 76.5%, 3.0%, 498 ms, 192 ms<br>• Group 3.a: 79.1%, 2.6%, 486 ms, 179 ms<br>• Group 3.b: 79.5%, 2.5%, 491 ms, 179 ms<br>• Group 4.a: 82.3%, 2.3%, 478 ms, 162 ms<br>• Group 4.b: 81.8%, 2.3%, 481 ms, 166 ms<br>CCT Congruent (%correct, %outlier, mean RTs, *SD* RTs):<br>• Group 1.a: 63.4%, 1.7%, 561 ms, 204 ms<br>• Group 1.b: 67.1%, 1.4%, 571 ms, 205 ms<br>• Group 2.a: 71.5%, 2.4%, 573 ms, 182 ms<br>• Group 2.b: 70.6%, 2.0%, 568 ms, 181 ms<br>• Group 3.a: 73.2%, 2.0%, 556 ms, 173 ms<br>• Group 3.b: 73.8%, 2.2%, 563 ms, 176 ms<br>• Group 4.a: 78.4%, 1.9%, 558 ms, 163 ms<br>• Group 4.b: 77.1%, 1.9%, 560 ms, 165 ms<br>CCT Incongruent (%correct, %outlier, mean RTs, *SD* RTs):<br>• Group 1.a: 55.8%, 1.5%, 676 ms, 233 ms<br>• Group 1.b: 59.5%, 0.8%, 687 ms, 222 ms<br>• Group 2.a: 57.9%, 0.6%, 695 ms, 201 ms<br>• Group 2.b: 56.8%, 0.8%, 700 ms, 196 ms<br>• Group 3.a: 59.8%, 0.8%, 677 ms, 190 ms<br>• Group 3.b: 60.2%, 0.8%, 684 ms, 192 ms<br>• Group 4.a: 65.7%, 0.6%, 685 ms, 168 ms<br>• Group 4.b: 64.1%, 0.7%, 683 ms, 172 ms<br>Mean diffusion model parameters<br>(variability in nondecision time, nondecision time (in sec), boundary separation, across-trial variability in drift rate, drift rate):<br>*CRT task:*<br>• Group 1.a: 0.112, −0.334, 0.285, 0.318, −0.395<br>• Group 1.b: 0.255, −0.372, 0.314, 0.38, −0.521<br>• Group 2.a: 0.163, 0.041, −0.016, 0.012, −0.056<br>• Group 2.b: 0.060, −0.056, 0.047, −0.066, −0.087<br>• Group 3.a: −0.045, 0.032, 0.014, 0.022, 0.031<br>• Group 3.b: −0.029, 0.04, −0.007, −0.029, 0.027<br>• Group 4.a: −0.116, 0.158, −0.092, −0.127, 0.227<br>• Group 4.b: −0.033, 0.175, −0.064, −0.084, 0.189<br>*CCT task:*<br>• Group 1.a: 0.279, −0.06, 0.022, 0.016, −0.333<br>• Group 1.b: 0.121, −0.147, 0.076, 0.061, −0.356<br>• Group 2.a: 0.098, 0.073, 0.072, 0.027, −0.071<br>• Group 2.b: 0.126, 0.016, 0.007, 0.155, −0.035<br>• Group 3.a: −0.005, −0.015, 0.014, 0.016, 0.022<br>• Group 3.b: 0.001, 0.038, 0.003, −0.029, 0.017<br>• Group 4.a: −0.138, 0.113, −0.078, −0.099, 0.185<br>• Group 4.b: −0.044, 0.135, −0.037, −0.001, 0.172<br>Note: Negative mean values for nondecision time and variability parameters are implausible (suggests potential misfits). Hierarchical DMs for two-choice response times (Vandekerckhove et al., 2011) was used to estimate the diffusion model parameters. |

*Note*. ADHD = attention-deficit/hyperactivity disorder.

(*Appendix continues*)

**Table A3**
*Summary of the Results and Sample Characteristics of Studies in the Test Domain: Selective Attention*

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Friedman-Hill et al. (2010) | *ADHD group:*<br>15 children aged between 8 and 13, $M_{age}$ = 10.3 years (*SD* = 1.5), 73% males. Subtype diagnoses based on *DSM–IV*: $N_{ADHD\text{-}C}$: 7, $N_{ADHD\text{-}I}$: 8. Comorbidities included: 9 children without any comorbid diagnosis, 3 children with Oppositional Defiant Disorder, and 3 children with Anxiety Disorder.<br>*Control children group:*<br>14 children aged between 8 and 13, $M_{age}$ = 11.6 years (*SD* = 1.2), 64% males. | Error rates and mean RTs across conditions:<br>*ADHD group:*<br>• "low difficulty, low distraction" - condition: 6.0%, 750 ms<br>• "low difficulty, medium distraction" - condition: 5.0%, 734 ms<br>• "low difficulty, high distraction" - condition: 6.0%, 710 ms<br>• "high difficulty, low distraction" - condition: 28.0%, 884 ms<br>• "high difficulty, medium distraction" - condition: 29.0%, 890 ms<br>• "high difficulty, high distraction" - condition: 26.0%, 900 ms<br>*Control children group:*<br>• "low difficulty, low distraction" - condition: 2.5%, 550 ms<br>• "low difficulty, medium distraction" - condition: 3.0%, 553 ms<br>• "low difficulty, high distraction" - condition: 2.0%, 530 ms<br>• "high difficulty, low distraction" - condition: 35.0%, 709 ms<br>• "high difficulty, medium distraction" - condition: 35.0%, 700 ms<br>"high difficulty, high distraction" - condition: 35.0%, 710 ms |
| Schneidt et al. (2018) | *ADHD group:*<br>36 adults aged between 19 and 53, $M_{age}$ = 36.81 years (*SD* = 10.82), 53% males. Comorbidities included: 11 adults with Depressive Disorder, 2 adults with Eating Disorders, 9 adults with Anxiety Disorders.<br>*Control group:*<br>37 adults aged between 19 and 60, $M_{age}$ = 37 years (*SD* = 11.43, 46% males. | Error rates and mean RTs across conditions:<br>*ADHD group:*<br>• "low difficulty, negative emotion" - condition: 5.6%, 1,036 ms<br>• "low difficulty, positive emotion" - condition: 4.9%, 921 ms<br>• "low difficulty, neutral emotion" - condition: 4.8%, 939 ms<br>• "high difficulty, negative emotion" - condition: 24.8%, 945 ms<br>• "high difficulty, positive emotion" - condition: 27.0%, 854 ms<br>• "high difficulty, neutral emotion" - condition: 26.3%, 838 ms<br>*Control group:*<br>• "low difficulty, negative emotion" - condition: 2.9%, 826 ms<br>• "low difficulty, positive emotion" - condition: 3.1%, 774 ms<br>• "low difficulty, neutral emotion" - condition: 2.9%, 748 ms<br>• "high difficulty, negative emotion" - condition: 24.5%, 791 ms<br>• "high difficulty, positive emotion" - condition: 24.0%, 722 ms<br>"high difficulty, neutral emotion" - condition: 23.8%, 735 ms |

(*Appendix continues*)

**Table A3** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Mulder et al. (2010) | *ADHD group:*<br>25 children, $M_{age}$ = 11.8 years ($SD$ = 3.1, 88% males. Diagnoses based on the Diagnostic Interview Schedule for Children, parent version (DISC-P). Subtypes: $N_{ADHD\text{-}I}$: 9, $N_{ADHD\text{-}H}$: 4, $N_{ADHD\text{-}C}$: 12. 7 children had a comorbid diagnosis of oppositional defiant disorder (ODD).<br>*Control group:*<br>30 children, $M_{age}$ = 12.9 years ($SD$ = 4.0, 70% males. | Mean diffusion model parameters across conditions:<br>*Control group (accuracy condition):*<br>• Boundary Separation (a): 0.184<br>• Drift rate (difficulty level 1): 0.007<br>• Drift rate (difficulty level 2): 0.146<br>• Drift rate (difficulty level 3): 0.174<br>• Drift rate (difficulty level 4): 0.269<br>• Drift rate (difficulty level 5): 0.432<br>• Nondecision time (in sec): 0.547<br>*ADHD group (accuracy condition):*<br>• Boundary Separation (a): 0.157<br>• Drift rate (difficulty level 1): 0.022<br>• Drift rate (difficulty level 2): 0.226<br>• Drift rate (difficulty level 3): 0.266<br>• Drift rate (difficulty level 4): 0.404<br>• Drift rate (difficulty level 5): 0.644<br>• Nondecision time (in sec): 0.541<br>*Control group (speed condition):*<br>• Boundary Separation (a): 0.089<br>• Drift rate (difficulty level 1): 0.031<br>• Drift rate (difficulty level 2): 0.509<br>• Drift rate (difficulty level 3): 0.604<br>• Drift rate (difficulty level 4): 0.928<br>• Drift rate (difficulty level 5): 1.489<br>• Nondecision time (in sec): 0.515<br>*ADHD group (speed condition):*<br>• Boundary Separation (a): 0.101<br>• Drift rate (difficulty level 1): 0.046<br>• Drift rate (difficulty level 2): 0.610<br>• Drift rate (difficulty level 3): 0.722<br>• Drift rate (difficulty level 4): 1.103<br>• Drift rate (difficulty level 5): 1.765<br>• Nondecision time (in sec): 0.522<br>Note: the Diffusion Model Analysis Toolbox in Matlab was used to estimate the diffusion model parameters. |
| Johnson et al. (2008) | *ADHD group:*<br>73 children (86% males, $M_{age}$ = 12.7 years, $SD$ = 2.3). *DSM–IV* subtype diagnosis: $N_{ADHD\text{-}I}$ = 10, $N_{ADHD\text{-}H}$ = 2, $N_{ADHD\text{-}C}$ = 61. Comorbidities included: 30 children with Oppositional Defiant Disorder, 8 children with Conduct Disorder. The ADHD group had a significantly lower IQ than the control group ($p < .05$).<br>*Control group:*<br>73 children (89% male, $M_{age}$ = 13.1 years, $SD$ = 1.9). | Error rates and mean RTs across conditions:<br>(error rates calculated based on median number of incorrect responses)<br>*ADHD group:*<br>• Neutral flanker type: 8.3%, 689 ms<br>• Congruent flanker type: 8.3%, 692 ms<br>• Incongruent flanker type: 19.0%, 850 ms<br>*Control group:*<br>• Neutral flanker type: 2.6% error rate, 586 ms<br>• Congruent flanker type: 2.1% error rate, 595 ms<br>Incongruent flanker type: 12.0% error rate, 730 ms |
| Epstein et al. (2011) | *ADHD group:*<br>104 children aged between 7 and 11.<br>*DSM–IV* subtype diagnoses. Sample characteristics by subtype:<br>ADHD-I:<br>$N$ = 53, $M_{age}$ = 8.35 years, $SD$ = 1.31, 64% males. Comorbidities included: Oppositional Defiant Disorder (ODD), ($N$ = 16), Anxiety Disorder ($N$ = 20), Mood Disorder ($N$ = 1). | Summary statistics (error rates, mean RTs, Coefficient of Variation (in ms), ex-Gaussian Tau Indicator in ms):<br>• ADHD-C group: 28.4%, 874 ms, 31.69, 211.5<br>• ADHD-I group: 14.4%, 767 ms, 28.47, 174.35<br>• Control group: 16.9%, 755ms, 24.79, 144.03<br>Note: measures were averaged over blocks with and without reward components. Coefficient of Variation is calculated as follows: RT standard deviation/mean RTs. |

(*Appendix continues*)

**Table A3** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| | ADHD-C:<br>$N = 51$, $M_{age} = 7.90$ years, $SD = 1.11$, 80% males. Comorbidities included: ODD ($N = 22$), Conduct Disorder ($N = 4$), Anxiety Disorder ($N = 18$), Mood Disorder ($N = 1$).<br>*Control group:*<br>47 children aged between 7 and 11 years, $M_{age} = 8.33$ years ($SD = 1.35$), 81% males. Comorbidities included: Anxiety Disorder ($N = 2$). | |
| Tegelbeckers et al. (2016) | *ADHD group:*<br>36 children aged between 8 and 13, $M_{age} = 10.61$ years ($SD = 1.61$), 86% males. *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I} = 6$, $N_{ADHD\text{-}C} = 29$, $N_{ADHD\text{-}H} = 1$. Comorbidities included: Oppositional Defiant Disorder ($N = 12$), Conduct Disorder ($N = 1$). The ADHD group had a significantly lower IQ than the control group ($p < .05$).<br>*Control group:*<br>36 children aged between 8 and 13 $M_{age} = 10.58$ years ($SD = 1.71$), 86% males. | Summary statistics across conditions:<br>(approximation from the figure)<br>*Standard sound condition:*<br>• Commission error rate: ADHD group: 15.0%, Control group: 9.0%<br>• Omission error rate: ADHD group: 2.5%, Control group: 0.3%<br>• Mean RTs: ADHD group: 580ms, Control group: 560ms<br>• Coefficient of Variation (in ms): ADHD group: 0.275, Control group: 0.21<br>*Novel sound condition:*<br>• Commission error rate: ADHD group: 11.5%, Control group: 6.0%<br>• Omission error rate: ADHD group: 2.0%, Control group: 0.9%<br>• Mean RTs: ADHD group: 600ms, Control group: 570ms<br>• Coefficient of Variation (in ms): ADHD group: 0.25, Control group: 0.21<br>*No sound condition:*<br>• Commission error rate: ADHD group: 12.0%, Control group: 6.0%<br>• Omission error rate: ADHD group: 5.0%, Control group: 2.0%<br>• Mean RTs: ADHD group: 650ms, Control group: 600ms<br>• Coefficient of Variation (in ms): ADHD group: 0.30, Control group: 0.225<br>Note: Coefficient of Variation is calculated as follows: RT standard deviation/mean RTs |
| Gohil et al. (2017) | *ADHD group:*<br>22 children aged between 11 and 12 $M_{age} = 11.38$ years ($SD = 1.6$), 91% males.<br>*Control group:*<br>25 age-matched children (72% males, $M_{age} = 11.45$ years, $SD = 1.5$). | Error rates across conditions:<br>(approximation from the figures)<br>*ADHD group:*<br>• "compatible primes, congruent flankers" - condition: 7.0%<br>• "incompatible primes, congruent flankers" - condition: 12.0%<br>• "compatible primes, incongruent flankers" - condition: 12.5%<br>• "incompatible primes, incongruent flankers" - condition: 16.0% |

(*Appendix continues*)

**Table A3** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| | | *Control group:*<br>• "compatible primes, congruent flankers" - condition: 2.5%<br>• "incompatible primes, congruent flankers" - condition: 4.0%<br>• "compatible primes, incongruent flankers" - condition: 4.0%<br>• "incompatible primes, incongruent flankers" - condition: 7.0%<br>Mean RTs for correct responses across conditions:<br>• "compatible primes" - condition: 498 ms<br>• "incompatible primes" - condition: 519 ms<br>• "congruent flankers" - condition: 497 ms<br>"incongruent flankers" - condition: 520 ms |
| Banich et al. (2009) | *ADHD group:*<br>23 subjects, 61% male, $M_{age}$ = 20.0 years ($SD$ = 1.7), all subjects diagnosed with ADHD-C based on *DSM–IV*. None of the subjects had any comorbidities.<br>*Control group:*<br>23 subjects, 57% male, $M_{age}$ = 19 years ($SD$ = .9). | mean RTs and accuracy across trial types:<br>(approximation from the figures)<br>*Congruent trials:*<br>• ADHD group: 690 ms (Accuracy: 96.0%)<br>• Control group: 720 ms (Accuracy: 97.0%)<br>*Incongruent trials:*<br>• ADHD group: 820 ms (Accuracy: 87.5%)<br>• Control group: 860 ms (Accuracy: 88.0%)<br>*Neutral trials:*<br>• ADHD group: 725 ms (Accuracy: 95.0%)<br>• Control group: 700 ms (Accuracy: 96.0%)<br>mean RTs and accuracy across trial types:<br>(approximation from the figures)<br>*Congruent trials:*<br>• ADHD group: 710 ms (Accuracy: 96.0%)<br>• Control group: 675 ms (Accuracy: 97.0%)<br>*Incongruent trials:*<br>• ADHD group: 720 ms (Accuracy: 97.5%)<br>• Control group: 700 ms (Accuracy: 98.0%)<br>*Neutral trials:*<br>• ADHD group: 700 ms (Accuracy: 95.0%)<br>Control group: 670 ms (Accuracy: 97.0%) |
| Hasler et al. (2016) | *ADHD group:*<br>21 subjects, 33% male, $M_{age}$ = 40.05 years ($SD$ = 9.5), all subjects diagnosed based on *DSM–IV*.<br>*Control group:*<br>20 subjects, 35% male, $M_{age}$ = 25.5 years ($SD$ = 4.0). | Mean RTs across trial types:<br>(approximation from the figures)<br>*Congruent trials:*<br>• ADHD group (no cue/center cue/spatial cue): 550 ms/540 ms/505 ms<br>• Control group (no cue/center cue/spatial cue): 550 ms/540 ms/510 ms<br>*Incongruent trials:*<br>• ADHD group (no cue/center cue/spatial cue): 650 ms/640 ms/585 ms<br>• Control group (no cue/center cue/spatial cue): 625 ms/610 ms/580 ms |

(*Appendix continues*)

**Table A3** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Merkt et al. (2013) | *ADHD group:*<br>15 female college students, $M_{age}$ = 30.20 years ($SD$ = 5.93). On average, participants were 29 years old when they received their ADHD diagnosis (based on *DSM–IV*). 3 subjects received the diagnosis before the age of 25, and none of them before the age of 20. 2 subjects had an additional diagnosis for personality disorder and anxiety. The ADHD group was significantly older than the control group ($p < .05$).<br>*Control group:*<br>24 female college students, $M_{age}$ = 22.58 years ($SD$ = 2.53). | Error rates and mean RTs across conditions: (approximation from the figures)<br>*Condition: frequent incongruent flankers, congruent*<br>• ADHD group: 2.0%, 675 ms<br>• Control group: 2.0%, 600 ms<br>*Condition: frequent incongruent flankers, incongruent*<br>• ADHD group: 3.0%, 700 ms<br>• Control group: 4.0%, 620 ms<br>*Condition: infrequent incongruent flankers, congruent*<br>• ADHD group: 2.0%, 650 ms<br>• Control group: 2.0%, 580 ms<br>*Condition: infrequent incongruent flankers, incongruent*<br>• ADHD group: 4.0%, 675 ms<br>• Control group: 7.0%, 620 ms<br>Mean diffusion model parameters across conditions:<br>*ADHD group:*<br>• Drift rates (frequent incongruent flankers congruent/incongruent): 3.9/2.3<br>• Drift rates (infrequent incongruent flankers congruent/incongruent): 3.9/2.9<br>• Boundary separation (frequent incongruent flankers): 1.5<br>• Boundary separation (infrequent incongruent flankers): 1.5<br>• Nondecision time (in sec) (frequent incongruent flankers): 0.49<br>• Nondecision time (in sec) (infrequent incongruent flankers): 0.46<br>*Control group:*<br>• Drift rates (frequent incongruent flankers congruent/incongruent): 4.5/3.2<br>• Drift rates (infrequent incongruent flankers congruent/incongruent): 4.1/2.8<br>• Boundary separation (frequent incongruent flankers): 1.25<br>• Boundary separation (infrequent incongruent flankers): 1.4<br>• Nondecision time (in sec) (frequent incongruent flankers): 0.46<br>Nondecision time (in sec) (infrequent incongruent flankers): 0.44<br>Note: Fast-dm software (Voss & Voss, 2007) was used to estimate the diffusion model parameters. |
| Weigard and Huang-Pollock (2014) | *ADHD group:*<br>72 children aged between 9 and 12, $M_{age}$ = 10.17 years ($SD$ = 1.02), 54% males. *DSM–IV* subtype diagnoses:<br>$N_{ADHD\text{-}I}$ = 40, $N_{ADHD\text{-}C}$ = 33, $N_{ADHD\text{-}H}$ = 5.<br>Comorbidities included: Oppositional Defiant Disorder (ODD) ($N$ = 23), Conduct Disorder ($N$ = 6), Depressive Disorder ($N$ = 6), Anxiety Disorder ($N$ = 10).<br>*Control group:*<br>36 children aged between 9 and 12, $M_{age}$ = 10.50 years ($SD$ = 1.16), 53% males. Comorbidities included: ODD<br>($N$ = 1), Anxiety Disorder ($N$ = 1). | Mean RTs (approximation from the figures)<br>*Epoch 1 (novel configuration/repeated configuration - conditions):*<br>• ADHD: (1,510ms/1,550ms), Control: (1,475 ms/1,475 ms)<br>*Epoch 2 (novel configuration/repeated configuration - conditions):*<br>• ADHD: (1,450ms/1,450ms), Control: (1,350 ms/1,350 ms)<br>*Epoch 3 (novel configuration/repeated configuration - conditions):*<br>• ADHD: (1,360ms/1,360ms), Control: (1,300 ms/1,250 ms) |

(*Appendix continues*)

**Table A3** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| | | Accuracy for the three epochs (approximation from the figures)<br>*Epoch 1 (novel configuration/repeated configuration - conditions):*<br>• ADHD: (95.1%/94.8%), Control: (96.9%/97.4%)<br>*Epoch 2 (novel configuration/repeated configuration - conditions):*<br>• ADHD: (95.2%/95.0%), Control: (97.2%/97.2%)<br>*Epoch 3 (novel configuration/repeated configuration - conditions):*<br>• ADHD: (95.0%/95.0%), Control: (97.8%/97.9%)<br>Mean diffusion model parameters across epochs and conditions:<br>*Epoch 1 (novel configuration/repeated configuration - conditions):*<br>• nondecision time (in sec): ADHD: (0.750/0.785), Control: (0.725/0.725)<br>• Drift rate: ADHD: (1.39/1.35), Control: (1.50/1.50)<br>• Boundary separation: ADHD: (2.37/2.35), Control: (2.43/2.49)<br>*Epoch 2 (novel configuration/repeated configuration - conditions):*<br>• nondecision time (in sec): ADHD: (0.700/0.725), Control: (0.650/0.650)<br>• Drift rate: ADHD: (1.47/1.44), Control: (1.60/1.65)<br>• Boundary separation: ADHD: (2.35/2.31), Control: (2.45/2.46)<br>*Epoch 3 (novel configuration/repeated configuration - conditions):*<br>• nondecision time (in sec): ADHD: (0.640/0.650), Control: (0.600/0.615)<br>• Drift rate: ADHD: (1.47/1.55), Control: (1.65/1.80)<br>• Boundary separation: ADHD: (2.37/2.37), Control: (2.52/2.41)<br>Notes: Data was grouped into three epochs. Fast-dm software (Voss & Voss, 2007) was used to estimate the diffusion model parameters. |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time.

(*Appendix continues*)

**Table A4**

*Summary of Results and Sample Characteristics of Studies in the Test Domain: Working Memory*

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Epstein et al. (2011) | *ADHD group:*<br>104 children aged between 7 and 11.<br>*DSM–IV* subtype diagnoses. Sample characteristics by subtype:<br>ADHD-I: $N$ = 53, $M_{age}$ = 8.35 years, $SD$ = 1.31, 64% males. Comorbidities included: Oppositional Defiant Disorder (ODD) ($N$ = 16), Anxiety Disorder ($N$ = 20), Mood Disorder ($N$ = 1).<br>ADHD-C: $N$ = 51, $M_{age}$ = 7.90 years, $SD$ = 1.11, 80% males. Comorbidities included: ODD ($N$ = 22), Conduct Disorder ($N$ = 4), Anxiety Disorder ($N$ = 18), Mood Disorder ($N$ = 1).<br>*Control group:*<br>47 children aged between 7 and 11 years, $M_{age}$ = 8.33 years ($SD$ = 1.35), 81% males. Comorbidities included: Anxiety Disorder ($N$ = 2). | Summary statistics<br>(error rates, mean RTs, Coefficient of Variation (in ms), ex-Gaussian Tau Indicator in ms):<br>• Control group: 18.1%, 829 ms, 30.99, 157.72<br>• ADHD-C group: 31.6%, 897 ms, 36.17, 247.36<br>• ADHD-I group: 27.9%, 873 ms, 33.20, 224.61<br>Note: measures were averaged over blocks with and without reward components. Coefficient of Variation is calculated as follows: RT standard deviation/mean RTs. |
| Stroux et al. (2016) | *ADHD group:*<br>40 participants aged between 19 and 50, $M_{age}$ = 30.15 years ($SD$ = 9.15), 53% males. *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$ = 22, $N_{ADHD\text{-}C}$ = 18.<br>*Control group:*<br>41 participants aged between 19 and 50, $M_{age}$ = 32.24 years ($SD$ = 9.36), 56% males. | 1-Back task<br>Accuracy rates:<br>• Control group: 82.0%<br>• ADHD group: 77.0%<br>2-Back task<br>Accuracy rates:<br>• Control group: 75.0%<br>• ADHD group: 65.0% |
| Kawabe et al. (2018) | *ADHD group:*<br>9 boys aged between 7 and 12, $M_{age}$ = 9.1 years ($SD$ = 2.1). Diagnoses based on *DSM–5*: 3 boys had a diagnosis of ADHD-only ($M_{age}$ = 10 years). 6 boys had a diagnosis of ADHD co-morbid autism ($M_{age}$ = 8.7 years).<br>*Control group:*<br>33 boys aged between 7 and 13, $M_{age}$ = 9.4 years ($SD$ = 1.7). | 1-Back task<br>Accuracy, mean RTs for correct responses:<br>• ADHD group: 61.8%, 1,065 ms<br>• Control group: 72.2%, 846 ms |
| Lenartowicz et al. (2014) | *ADHD group:*<br>37 children aged between 7 and 14, $M_{age}$ = 10.2 years ($SD$ = n.a.), 65% males. *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$ = 15, $N_{ADHD\text{-}C}$ = 22.<br>*Control group:*<br>43 children aged between 7 and 14, $M_{age}$ = 10.6 years ($SD$ = n.a.), 60% males. | Error rates and mean RTs:<br>• ADHD group: 24.0%, 1,400 ms<br>• Control group: 19.0%, 1,300 ms |
| Weigard and Huang-Pollock (2017) | *ADHD group:*<br>71 children aged between 8 and 12, 65% males.<br>*Control group:*<br>27 children aged between 8 and 12, 37% males. | Accuracy of correctly recalled items in the span digit task:<br>• ADHD group: 25.0%<br>• Control group: 43.0%<br>Mean diffusion model parameters for the numerosity task: (approximation from the figures)<br>*Difficult condition:*<br>• ADHD group: boundary separation: 1.62, nondecision time (in sec): 0.298, drift rate: 0.58<br>• Control group: boundary separation: 1.59, nondecision time (in sec): 0.325, drift rate: 0.78<br>*Easy condition:*<br>• ADHD group: boundary separation: 1.71, nondecision time (in sec): 0.31, drift rate: 1.10<br>• Control group: boundary separation: 1.75, nondecision time (in sec): 0.34, drift rate: 1.70<br>Note: Fast-dm software (Voss & Voss, 2007) was used to estimate the diffusion model parameters. |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time.

(*Appendix continues*)

**Table A5**
*Summary of the Results and Sample Characteristics of Studies in the Test Domain: Time Perception*

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Valko et al. (2010) | *ADHD adult group:*<br>22 adults aged between 32 and 52, $M_{age}$ = 42.2 years ($SD$ = 4.4), 50% males. 12 adults met criteria for additional clinical psychopathological symptoms.<br>*ADHD children group:*<br>33 children aged between 8 and 15, $M_{age}$ = 11 years, ($SD$ = 2.1), 61% males. All children were diagnosed with ADHD-C based on *DSM–IV*. Comorbidities included: Oppositional Defiant Disorder ($N$ = 11), Depressive Disorder ($N$ = 3), Anxiety Disorder ($N$ = 2).<br>*Control adult group:*<br>22 adults aged between 32 and 52, $M_{age}$ = 43.5 years ($SD$ = 4.5), 50% males.<br>*Control children group:*<br>33 age- gender- and IQ matched children, $M_{age}$ = 11.0 years ($SD$ = 2.1), 61% males. | Time Reproduction task:<br>absolute discrepancies between target intervals and mean reproduction time<br>*ADHD children group:*<br>• 2-sec interval: 253ms, 4-sec interval: 506 ms<br>• 6-sec interval: 713 ms, 8-sec interval: 968 ms<br>*ADHD adult group:*<br>• 2-sec interval: 226 ms, 4-sec interval: 427 ms<br>• 6-sec interval: 605 ms, 8-sec interval: 809 ms<br>*Control children group:*<br>• 2-sec interval: 196 ms, 4-sec interval: 270 ms<br>• 6-sec interval: 412 ms, 8-sec interval: 502 ms<br>*Control adult group:*<br>• 2-sec interval: 179 ms, 4-sec interval: 270 ms<br>• 6-sec interval: 409 ms, 8-sec interval: 504 ms<br>Time Discrimination task:<br>Hits and mean RTs<br>*Difference in stimuli duration smaller or equal than 100 ms:*<br>• ADHD children group: 20.9, 1,322 ms<br>• ADHD adult group: 24.0, 1,281 ms<br>• Control children group: 22.2, 1,453 ms<br>• Control adult group: 26.0, 951 ms<br>*Difference in stimuli duration greater or equal than 200 ms:*<br>• ADHD children group: 27.0, 1,105 ms<br>• ADHD adult group: 32.0, 906 ms<br>• Control children group: 30.2, 1,168 ms<br>Control adult group: 33.6, 682 ms |
| Marx et al. (2017) | *ADHD group:*<br>16 boys aged between 8 and 13, $M_{age}$ = 10.6 years ($SD$ = 1.6). *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$ = 7, $N_{ADHD\text{-}H}$ = 3, $N_{ADHD\text{-}C}$ = 6. Comorbidities included: Reactive Attachment Disorder ($N$ = 1), Specific Reading Disorder ($N$ = 2), Nonorganic Enuresis ($N$ = 2) and Encopresis ($N$ = 2).<br>*Control group:*<br>18 boys aged between 8 and 13, $M_{age}$ = 9.5 years ($SD$ = 1.5). The controls had no psychiatric disorders according to *DSM–IV*. | Summary statistics (from first session in which all participants had to abstain from ADHD stimulants).<br>Time Discrimination:<br>*Mean Sensitivity threshold (SD)*<br>• ADHD group: 231ms (68 ms)<br>• Control group: 218ms (56ms)<br>Time Estimation:<br>*Mean Absolute error with SD in parentheses*<br>• ADHD group: 5,833ms (3,557 ms)<br>• Control group: 3,574ms (2,610 ms)<br>Time Production:<br>*Mean Absolute error with SD in parentheses*<br>• ADHD group: 6,339ms (1,977 ms)<br>• Control group: 3,832ms (2,091 ms)<br>Time Reproduction:<br>*Mean Absolute error with SD in parentheses*<br>• ADHD group: 5,339ms (3,468 ms)<br>• Control group: 3,084ms (1,119 ms)<br>*point at which two targets that differ in their presentation duration are perceived as being of equal length. |

(*Appendix continues*)

**Table A5** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Shapiro and Huang-Pollock (2019) | *ADHD group:*<br>50 children aged between 8 and 12, $M_{age}$ = 9.26 years ($SD$ = 1.14), 62% males. Diagnoses based on *DSM–IV*. Comorbidities included: Oppositional Defiant Disorder/ Conduct Disorder ($N$ = 29), Depressive Disorder/Dysthymic Disorder ($N$ = 5), Anxiety Disorder ($N$ = 6).<br>*Control group:*<br>32 children aged between 8 and 12, $M_{age}$ = 9.28 years ($SD$ = 1.17), 50% males. | Bisection task outcomes:<br>• Bisection point: ADHD: 3.51, Control: 3.53<br>• Difference limen: ADHD: 800.44, Control: 565.33<br>• Bisection coefficient of variation: ADHD: 0.23, Control: 0.16<br>• RTs: ADHD: 118ms, Control: 111 ms<br>Mean diffusion model parameters (short vs. long durations):<br>Medians and 95% Credible Intervals [CI]<br>*Boundary separation (constant across stimulus types):*<br>• ADHD: 2.06 [1.97, 2.15], Control: 2.01 [1.82, 2.16]<br>• *Variability in nondecision time (in sec) (constant across stimulus types):* ADHD: 0.18 [0.09, 0.25], Control: 0.18 [0.10, 0.25]<br>*Variability in starting point (constant across stimulus types):*<br>• ADHD: 0.21 [0.11, 0.32], Control: 0.21 [0.11, 0.31]<br>*Across-trial variability in drift rate (constant across stimulus types):*<br>• ADHD: 0.14 [0.07, 0.19], Control: 0.14 [0.07, 0.19]<br>Short duration:<br>*Nondecision time (in sec):*<br>• ADHD: 0.27 [0.24, 0.30], Control: 0.25 [0.22, 0.28]<br>• ADHD: 0.47 [0.47, 0.48], Control: 0.50 [0.47, 0.52]<br>*Drift rate (second stage of the decision process):*<br>• ADHD: 0.85 [0.77, 0.94], Control: 1.04 [0.94, 1.14]<br>Long duration:<br>*Nondecision time (in sec):*<br>• ADHD: 0.25 [0.23, 0.27], Control: 0.24 [0.21, 0.27]<br>*Starting point:*<br>• ADHD: 0.54 [0.52, 0.55], Control: 0.55 [0.53, 0.58]<br>*Drift rate (second stage of the decision process):*<br>ADHD: 0.83 [0.73, 0.93], Control: 0.95 [0.84, 1.06]<br>Notes: the task involved classifying auditory stimuli into "short" or "long" durations. The software R (with inhouse code) was used to estimate the diffusion model parameters and the parameters related to the Bisection task within a Bayesian framework. Coefficient of variation is calculated as follows: RT standard deviation/ mean RTs. |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time.

(*Appendix continues*)

**Table A6**
*Summary of the Results and Sample Characteristics of Studies in the Test Domain: Sustained Attention*

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Collings (2003) | *ADHD group:*<br>46 boys aged between 8 and 10. Diagnoses based on *DSM–IV*: 35 boys had a diagnosis of ADHD-C ($M_{age}$ = 8.95 years). 11 boys had a diagnosis of ADHD-I ($M_{age}$ = 9.33 years). Children with comorbid diagnosis were excluded from the study.<br>*Control group:*<br>24 boys aged between 8 and 10, $M_{age}$ = 8.84 years (*SD* = .75). | Commission and omission error rates across conditions:<br>*1-sec ISI condition:*<br>• ADHD-C group: 2.9%, 8.7%<br>• ADHD-I group: 3.4%, 3.6%<br>• Control group: 3.7%, 5.9%<br>*2-sec ISI condition:*<br>• ADHD-C group: 4.3%, 10.9%<br>• ADHD-I group: 5.5%, 4.5%<br>• Control group: 2.0%, 5.9%<br>*4-sec ISI condition:*<br>• ADHD-C group: 3.5%, 7.1%<br>• ADHD-I group: 4.1%, 2.2%<br>Control group: 2.2%, 3.3% |
| Baytunca et al. (2018) | *ADHD group:*<br>41 children, 85.4% male, $M_{age}$ = 10.88 years (*SD* = 1.96). *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$: 24, $N_{ADHD\text{-}C}$: 17.<br>*ADHD + SCT group:*<br>42 children, 54.8% male, $M_{age}$ = 9 years (*SD* = 1.18). *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$: 24, $N_{ADHD\text{-}C}$: 18.<br>Subjects needed to have a minimum of 4 SCT symptoms rated by parents and teachers, respectively. There were significantly more females in this group than in the other groups ($p < .05$).<br>*Control group:*<br>24 children, 75% male, $M_{age}$ = 10.88 years (*SD* = 1.36). | Accuracy and mean RTs for correct responses:<br>• ADHD group: 90.0%, mean RTs = 523 ms<br>• ADHD and SCT group: 89.9%, mean RTs = 603 ms<br>• Control group: 98.0%, mean RTs = 471 ms<br>Error rate of omission errors:<br>• ADHD group: 9.9%<br>• ADHD and SCT group: 10.2%<br>• Control group: 1.8%<br>Error rate of commission errors:<br>• ADHD group: 2.7%<br>• ADHD and SCT group: 6.3%<br>• Control group: 1.2% |
| Huang-Pollock et al. (2012) | n.a. (meta-analysis of CPT performance). | Diffusion Decision Model Analysis:<br>*Mean drift rate (with SD in parentheses):*<br>• ADHD group: 0.18 (0.11)<br>• Control group: 0.28 (0.16)<br>*Mean boundary separation (with SD in parentheses):*<br>• ADHD group: 0.11 (0.03)<br>• Control group: 0.12 (0.04)<br>*Mean nondecision time component (with SD in parentheses):*<br>• ADHD group: 0.38 (0.11)<br>• Control group: 0.37 (0.09)<br>Note: EZ-diffusion modeling technique (Wagenmakers et al., 2007) was used to estimate the diffusion model parameters. |
| Huang-Pollock, Ratcliff, et al. (2020) | Between-subject experimental design:<br>Slow event rate + easy discrimination task:<br>*ADHD sample:* 45 children, 69% males, $M_{age}$ = 10.3 years (*SD* = 1.2). Diagnoses based on *DSM–IV*. Comorbidities included: Oppositional Defiant Disorder (ODD) and Conduct Disorder (CD) (*N* = 28), Major Depressive Disorder (MDD) (*N* = 5), Generalized Anxiety Disorder (GAD) (*N* = 7). *Control sample:* 20 children, 35% males, $M_{age}$ = 10.1 years (*SD* = 1.1). Diagnoses based on *DSM–IV*, which included ODD/CD (*N* = 1).<br>Slow event rate + hard discrimination task:<br>*ADHD sample:* 20 children, 70% males, $M_{age}$ = 9.4 years (*SD* = 1.2). Diagnoses based on *DSM–IV*. Comorbidities included: ODD/CD (*N* = 12), MDD (*N* = 4), GAD (*N* = 2).<br>*Control sample:* 20 children, 60% males, $M_{age}$ = 10.1 years (*SD* = .9). No diagnoses based on *DSM–IV*.<br>Fast event rate + easy discrimination task:<br>*ADHD sample:* 63 children, 64% males, $M_{age}$ = 10.0 years (*SD* = 1.3). Diagnoses based on *DSM–IV*. Comorbidities included: ODD/CD (*N* = 30), MDD (*N* = 5), GAD (*N* = 5). | Summary Statistics (for blocks 1–5 of the CPT)<br>Slow event rate + easy discrimination task:<br>*Accuracy, mean RTs, SD-RTs*<br>• ADHD group: 75.1%, 793 ms, 220 ms; Control group: 77.8%, 748 ms, 180 ms<br>Slow event rate + hard discrimination task:<br>*Accuracy, mean RTs, SD-RTs*<br>• ADHD group: 66.1%, 780 ms, 236 ms; Control group: 68.8%, 716 ms, 203 ms<br>Fast event rate + easy discrimination task:<br>*Accuracy, mean RTs, SD-RTs*<br>• ADHD group: 71.2%, 707 ms, 229 ms; Control group: 75.8%, 662 ms, 175 ms<br>Diffusion Decision Model Analysis (for blocks 1–5 of the CPT)<br>Slow event rate + easy discrimination task:<br>*Boundary separation, nondecision time (in sec), drift rate for go trials, drift rate for no-go trials, response bias towards go responses*<br>• ADHD group: 0.20, 0.44, 0.25, −0.33, 0.52<br>• Control group: 0.22, 0.46, 0.31, −0.45, 0.58<br>Slow event rate + hard discrimination task: |

(*Appendix continues*)

**Table A6** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| | *Control sample:* 19 children, 42% males, $M_{age}$ = 9.5 years (*SD* = 1.3). Diagnoses based on *DSM–IV*, which included ODD/CD (*N* = 1). | *Boundary separation, nondecision time, drift rate for go trials, drift rate for no-go trials, response bias towards go responses*<br>• ADHD group: 0.17, 0.46, 0.20, −0.19, 0.52<br>• Control group: 0.16, 0.45, 0.27, −0.28, 0.53<br>Fast event rate + easy discrimination task:<br>*Boundary separation, nondecision time, drift rate for go trials, drift rate for no-go trials, response bias towards go responses*<br>• ADHD group: 0.19, 0.39, 0.24, −0.29, 0.54<br>• Control group: 0.18, 0.42, 0.30, −0.36, 0.59<br>Summary Statistics (for blocks 6–10 of the CPT)<br>Slow event rate + easy discrimination task:<br>*Accuracy, mean RTs, SD-RTs*<br>• ADHD group: 75.6%, 834 ms, 217 ms; Control group: 77.7%, 810 ms, 185 ms<br>Slow event rate + hard discrimination task:<br>*Accuracy, mean RTs, SD-RTs*<br>• ADHD group: 68.5%, 792 ms, 244 ms; Control group: 72.8%, 753 ms, 203 ms<br>Fast event rate + easy discrimination task:<br>*Accuracy, mean RTs, SD-RTs*<br>• ADHD group: 72.8%, 736 ms, 232 ms; Control group: 77.4%, 705 ms, 172 ms<br>Diffusion Decision Model Analysis (for blocks 6–10 of the CPT)<br>Slow event rate + easy discrimination task:<br>*Boundary separation, nondecision time (in sec), drift rate for go trials, drift rate for no-go trials, response bias towards go responses*<br>• ADHD group: 0.20, 0.46, 0.24, −0.36, 0.46<br>• Control group: 0.19, 0.48, 0.31, −0.36, 0.46<br>Slow event rate + hard discrimination task:<br>*Boundary separation, nondecision time, drift rate for go trials, drift rate for no-go trials, response bias towards go responses*<br>• ADHD group: 0.17, 0.45, 0.18, −0.25, 0.48<br>• Control group: 0.17, 0.46, 0.29, −0.33, 0.48<br>Fast event rate + easy discrimination task:<br>*Boundary separation, nondecision time, drift rate for go trials, drift rate for no-go trials, response bias towards go responses*<br>• ADHD group: 0.20, 0.41, 0.24, −0.34, 0.51<br>• Control group: 0.19, 0.41, 0.35, −0.38, 0.49<br>Note: Fortran code (Inhouse code by Roger Ratcliff) was used to estimate the diffusion model parameters. |
| Loo et al. (2009) | *ADHD group:*<br>38 adults, 53% males, $M_{age}$ = 45.0 years (*SD* = 6.0). *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$ = 14, $N_{ADHD\text{-}H}$ = 4, $N_{ADHD\text{-}C}$ = 20. Comorbidities included: Any Mood Disorders (*N* = 24), Any Anxiety Disorders (*N* = 21), Oppositional Defiant Disorder or Conduct Disorder (*N* = 12) and Substance Use Disorders (*N* = 16).<br>*Control group:* 42 adults, 50% males, $M_{age}$ = 46.0 years (*SD* = 5.4). The controls had the following psychiatric disorders according to *DSM–IV*: Any Mood Disorders (*N* = 13), Any Anxiety Disorders (*N* = 13), and Substance Use Disorders (*N* = 7). | Summary statistics<br>*Mean number of omission errors (SD in parentheses)*<br>• ADHD group: 53.47 (13.69)<br>• Control group: 53.14 (12.49)<br>*Mean number of commission errors (SD in parentheses)*<br>• ADHD group: 50.95 (10.34)<br>• Control group: 46.99 (9.31)<br>*Mean RTs for correct responses (SD in parentheses)*<br>• ADHD group: 5,450 ms (1,361ms)<br>• Control group: 5,700 ms (1,130ms)<br>*RT variability (SD in parentheses)*<br>• ADHD group: 5,759 ms (1,245ms)<br>• Control group: 5,835 ms (1,195ms) |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time; SCT = sluggish cognitive tempo.

(*Appendix continues*)

**Table A7**
*Summary of the Results and Sample Characteristics of Studies in the Test Domain: Inhibitory Control*

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Epstein et al. (2011) | *ADHD group:*<br>104 children aged between 7 and 11.<br>*DSM–IV* subtype diagnoses. Sample characteristics by subtype:<br>ADHD-I: $N = 53$, $M_{age} = 8.35$ years, $SD = 1.31$, 64% males. Comorbidities included: Oppositional Defiant Disorder (ODD), ($N = 16$), Anxiety Disorder ($N = 20$), Mood Disorder ($N = 1$). ADHD-C: $N = 51$, $M_{age} = 7.90$ years, $SD = 1.11$, 80% males. Comorbidities included: ODD ($N = 22$), Conduct Disorder ($N = 4$), Anxiety Disorder ($N = 18$), Mood Disorder ($N = 1$).<br>*Control group:*<br>47 children aged between 7 and 11 years, $M_{age} = 8.33$ years ($SD = 1.35$), 81% males. Comorbidities included: Anxiety Disorder ($N = 2$). | Summary statistics<br>(error rates, mean RTs, Coefficient of Variation (in ms), ex-Gaussian Tau Indicator in ms):<br>• Control group: 9.6%, 899 ms, 30.99, 161.51<br>• ADHD-C group: 20.9%, 893 ms, 36.53, 251.65<br>• ADHD-I group: 16.1%, 806 ms, 34.57, 225.50<br>Note: coefficient of variation is calculated as follows: RT standard deviation/mean RTs |
| Baytunca et al. (2018) | *ADHD group:*<br>41 children, 85.4% male, $M_{age} = 10.9$ years ($SD = 2.0$). *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$: 24, $N_{ADHD\text{-}C}$: 17.<br>*ADHD + SCT group:*<br>42 children, 54.8% male, $M_{age} = 9$ years ($SD = 1.18$). *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$: 24, $N_{ADHD\text{-}C}$: 18. Subjects needed to have a minimum of 4 SCT symptoms rated by parents and teachers, respectively. There were significantly more females in this group than in the other groups ($p < .05$).<br>*Control group:*<br>24 children, 75% male, $M_{age} = 10.88$ years ($SD = 1.36$). | Mean RTs for simple condition:<br>(Instruction: press key whenever a stimulus appears on the screen)<br>• ADHD group: 553 ms<br>• ADHD + SCT group: 452 ms<br>• Control group: 446 ms<br>Mean RTs for complex condition:<br>(Instruction: see our description in the main text)<br>• ADHD group: 891ms<br>• ADHD + SCT group: 858 ms<br>• Control group: 792 ms<br>Rate of commission errors:<br>• ADHD group: 3.7%<br>• ADHD + SCT group: 6.8%<br>Control group: 2.4% |
| Wiersema et al. (2006) | *ADHD group:*<br>22 children, 64% male, $M_{age} = 10.3$ years ($SD = 1.6$). All children had a *DSM–IV* subtype diagnosis of ADHD-C. Comorbidities included Oppositional Defiant Disorder ($N = 9$) and Conduct Disorder ($N = 1$).<br>*Control group:*<br>15 children, 75% male, $M_{age} = 10.2$ years ($SD = 2.0$). No diagnosis of any mental-health disorders based on *DSM–IV*. | Summary statistics:<br>Condition with short ISIs:<br>*Mean RTs, SD-RTs, errors of commission:*<br>• ADHD group = 535 ms, 193 ms, 37%<br>• Control group = 570 ms, 150 ms, 21%<br>Condition with long ISIs:<br>*Mean RTs, SD-RTs, errors of commission:*<br>• ADHD group = 645 ms, 227 ms, 20%<br>• Control group = 607 ms, 168 ms, 20% |
| Mowinckel et al. (2015) | n.a. (meta-analysis of CPT performance). Mowinckel et al.'s Supplemental Material include Tables with sample characteristics of the different studies that were included in the meta-analysis. | Summary statistics<br>(Hedges' $g$ effect sizes for group-specific differences between controls and those with ADHD):<br>*Omission errors, commission errors, RTs, RT variability (i.e., RT variance)*<br>• Hedges' $g$ = .41, 0.41, −0.09, 0.40<br>Diffusion decision model analysis<br>(Hedges' $g$ effect sizes for group-specific differences between controls and those with ADHD):<br>*Boundary separation, drift rate (approximations from the figures)*<br>• Hedges' $g$ = .99, −1.60<br>Note: EZ-diffusion modeling technique (Wagenmakers et al., 2007) was used to estimate the diffusion model parameters. Hedge's $g$ effect sizes (rather than parameter estimates) are provided in the manuscript |

(*Appendix continues*)

**Table A7** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Lee et al. (2015) | *ADHD group:*<br>44 children aged between 9 to 14 (61% male, mean age = 11.16 years, *SD* = 1.57), with subtype diagnosis of ADHD-I (*N* = 14) or ADHD-C (*N* = 30) according to *DSM–IV*. Comorbid diagnosis included ODD (*N* = 16) and specific phobia (N = 3). The ADHD group had a significantly lower IQ than the control group ($p < .001$).<br><br>*Control group:*<br>31 children aged between 9 and 14 (35% male, mean age = 11.23 years, *SD* = 1.44). | Summary Statistics:<br>Fixed ISI - condition:<br>*Omission error rate/Commission error rate/mean RTs:*<br>• ADHD group = 4.6%/33.3%/436 ms<br>• Control group = 1.9%/22.1%/455 ms<br>*Coefficient of variation (in ms):*<br>• ADHD group = .42<br>• Control group = .30<br>*Ex-Gaussian model parameters: mu/sigma/tau (in ms):*<br>• ADHD group = 296.04/63.38/139.62<br>• Control group = 354.36/59.46/100.88<br>Jittered ISI - condition:<br>*Omission error rate/Commission error rate/mean RTs:*<br>• ADHD group = 3.7%/34.6%/432 ms<br>*Coefficient of variation (in ms):*<br>• ADHD group = .31<br>• Control group = .26<br>*Ex-Gaussian model parameters: mu/sigma/tau (in ms):*<br>• ADHD group = 324.05/55.08/107.90<br>• Control group = 369.27/55.53/95.08<br>Note: Coefficient of Variation is calculated as follows: RT standard deviation/mean RTs. |
| Huang-Pollock, Ratcliff, et al. (2017) | Between-Subjects Experimental Design:<br>Condition 1: slow event rate<br>*ADHD group:*<br>46 children, $M_{age}$ = 10.35 years (*SD* = 2.26), 67% males. *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$: 21, $N_{ADHD\text{-}C}$: 25. Comorbidities included: Oppositional Defiant Disorder (ODD), (*N* = 22), Conduct Disorder (*N* = 7), Anxiety Disorder (*N* = 6), Depressive Disorder (*N* = 2), Dysthymic Disorder (*N* = 2).<br>*Control group:*<br>21 children, $M_{age}$ = 10.12 years (*SD* = 1.28), 29% males. 1 child diagnosed with ODD.<br>Condition 2: fast event rate<br>*ADHD group:*<br>51 children, $M_{age}$ = 9.95 years (*SD* = 1.34), 65% males. *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$: 22, $N_{ADHD\text{-}C}$: 27, $N_{ADHD\text{-}H}$: 2. Comorbidities included: ODD (*N* = 19), Conduct Disorder (*N* = 3), Anxiety Disorder (*N* = 3), Depressive Disorder (*N* = 2), Dysthymic Disorder (*N* = 1).<br>*Control group:*<br>18 children, $M_{age}$ = 9.64 years, (*SD* = 1.29), 39% males. 1 child diagnosed with ODD. | Summary statistics across conditions:<br>*"Slow event rate"-condition:*<br>• Accuracy: ADHD group: 88.0%, Control group: 93.0%<br>• Omission error rate: ADHD group: 7.0%, Control group: 3.0%<br>• Commission error rate: ADHD group: 25.0%, Control group: 20.0%<br>• Mean RTs: ADHD group: 682 ms, Control group: 644 ms<br>*"Fast event rate"-condition:*<br>• Accuracy: ADHD group: 86.0%, Control group: 91.0%<br>• Omission error rate: ADHD group: 4.0%, Control group: 2.0%<br>• Commission error rate: ADHD group: 44.0%, Control group: 29.0%<br>• Mean RTs: ADHD group: 588 ms, Control group: 585 ms |

(*Appendix continues*)

**Table A7** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| | | Mean diffusion model parameters across conditions:<br>*"Slow event rate"-condition:*<br>• Nondecision time (in sec): ADHD group: 0.415, Control group: 0.437<br>• Boundary separation: ADHD group: 0.162, Control group: 0.160<br>• Starting point: ADHD group: 0.092, Control group: 0.100<br>• Drift rates<br>for 'go'-trials: ADHD group: 0.238, Control group: 0.285<br>for 'no-go'-trials: ADHD group: −0.157, Control group: −0.197<br>*"Fast event rate"-condition:*<br>• Nondecision time (in sec): ADHD group: 0.393, Control group: 0.403<br>• Boundary separation: ADHD group: 0.152, Control group: 0.152<br>• Starting point: ADHD group: 0.103, Control group: 0.105<br>• Drift rates<br>for 'go'-trials: ADHD group: 0.223, Control group: 0.250<br>for 'no-go'-trials: ADHD group: −0.109, Control group: −0.198<br>Note: Fortran code (Inhouse code by Roger Ratcliff) was used to estimate the diffusion model parameters. |
| Weigard et al. (2018) | *ADHD group:*<br>80 children, $M_{age}$ = 9.43 years (*SD* = 1.24), 65% males. *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$: 36, $N_{ADHD\text{-}C}$: 42, $N_{ADHD\text{-}H}$: 2. Comorbidities included:<br>Oppositional Defiant Disorder (ODD) (*N* = 34), Conduct Disorder (*N* = 8), Depressive Disorder (*N* = 4), Anxiety Disorder (*N* = 6).<br>*Control group:*<br>32 children, $M_{age}$ = 9.03 years (*SD* = 1.28), 44% males. 2 children were diagnosed with ODD. | Summary statistics across conditions:<br>High difficulty condition (response: "many"/response: "few"):<br>*Mean RTs:*<br>• ADHD group: (1,041 ms/1,092 ms)<br>• Control group: (892 ms/951 ms)<br>*RT standard deviation:*<br>• ADHD group: (406 ms/434 ms)<br>• Control group: (322 ms/329 ms)<br>*Accuracy:*<br>• ADHD group: (77.3%/78.3%)<br>• Control group: (85.8%/81.0%)<br>*Median drift rate for correct evidence (approximations from figures):*<br>• ADHD group: 3.9<br>• Control group: 4.5<br>*Median drift rate for error evidence (approximations from figures):*<br>• ADHD group: 2.1<br>• Control group: 2.1<br>Low difficulty condition (response: "many"/response: "few"):<br>*Mean RTs:*<br>• ADHD group: (947 ms/995 ms)<br>• Control group: (764 ms/846 ms)<br>*RT standard deviation:*<br>• ADHD group: (360 ms/396 ms)<br>• Control group: (222 ms/286 ms)<br>*Accuracy:*<br>• ADHD group: (91.9%/92.2%)<br>• Control group: (95.0%/96.5%) |

(*Appendix continues*)

**Table A7** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| | | *Median drift rate for correct evidence (approximations from figures):*<br>• ADHD group: 4.5<br>• Control group: 5.3<br>*Median drift rate for error evidence (approximations from figures):*<br>• ADHD group: 0.5<br>• Control group: 0.9<br>*(continued on next page)*<br>LBA model parameters that were kept constant across conditions, approximations from the figures):<br>*Median nondecision time component:*<br>• ADHD group: 0.1<br>• Control group: 0.2<br>*Median boundary separation for responses "many":*<br>• ADHD group: 1.8<br>• Control group: 1.5<br>*Median boundary separation for responses "few":*<br>• ADHD group: 0.1<br>Control group: 0.2 |
| Kingery (2017) | *ADHD group:*<br>25 children aged between 7 and 12, $M_{age}$ = 9.36 years (*SD* = 1.60), 64% males. Diagnoses based on *DSM–IV* (subtype distribution: n.a.). Comorbidities included: Oppositional Defiant Disorder (N = 3). The control group had significantly higher IQ scores than the ADHD group ($p <$ .05).<br>*Control group:*<br>26 children aged between 7 and 12, $M_{age}$ = 9.23 years (*SD* = 1.63), 62% males. | Summary statistics:<br>*Ex-Gaussian model parameter Tau (in ms):*<br>• ADHD group = 197.62, Control group = 162.55<br>*Mean RTs:*<br>• ADHD group = 528 ms, Control group = 507 ms<br>*RT standard deviation:*<br>• ADHD group = 193 ms, Control group = 169 ms<br>*Percentage of omission errors:*<br>• ADHD group = 15.7%, Control group = 6.8%<br>*Percentage of commission errors:*<br>ADHD group = 15.1%, Control group = 12.8% |
| Senderecka et al. (2012) | *ADHD group:*<br>20 children, 80% males, $M_{age}$ = 9.0 years (*SD* = 1.60), 64% males. Diagnoses based on *DSM–IV* with subtype ADHD-C. Comorbidities such as: Oppositional Defiant Disorder, Conduct Disorder, or any Anxiety, Tic, or Affective Disorders were excluded.<br>*Control group:*<br>20 children, 80% males, $M_{age}$ = 9.50 years (*SD* = 2.00), 64% males. | Summary Statistics:<br>*Mean RTs for go trials, error rate for go trials, latency of the stop process (SSRT):*<br>• ADHD group = 857 ms, 5.3%, 638 ms<br>• Control group = 704 ms, 1.4%, 453 ms |
| Kofler et al. (2018) | *ADHD group:*<br>77 children aged between 8 and 13, $M_{age}$ = 10.37 years (*SD* = 1.48), 65% males. *DSM–5* subtype diagnoses: $N_{ADHD\text{-}I}$: 30, $N_{ADHD\text{-}C}$: 42, $N_{ADHD\text{-}H}$: 5. Comorbidities included: Oppositional Defiant Disorder (10.5%), Autism Spectrum Disorder (2.6%), Anxiety Disorder (17.1%), Depressive Disorder (10.5%).<br>*Control group:*<br>40 children, $M_{age}$ = 10.67 years (*SD* = 1.58), 60% males. 24 neurotypical children and 16 children with other psychiatric disorders than ADHD. | Mean RTs (MRT) and stop-signal delays (SSD) across blocks:<br>*MRT block 1:*<br>• ADHD group: 604 ms, Control group: 604 ms<br>*MRT block 2:*<br>• ADHD group: 606 ms, Control group: 637 ms<br>*MRT block 3:*<br>• ADHD group: 605 ms, Control group: 635 ms<br>*MRT block 4:*<br>• ADHD group: 607 ms, Control group: 643 ms<br>*SSD block 1:*<br>• ADHD group: 270 ms, Control group: 303 ms<br>*SSD block 2:*<br>• ADHD group: 261 ms, Control group: 304 ms<br>*SSD block 3:*<br>• ADHD group: 265 ms, Control group: 302 ms<br>*SSD block 4:*<br>ADHD group: 263 ms, Control group: 301 ms |

(*Appendix continues*)

**Table A7** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Fosco et al. (2018) | *ADHD group:*<br>81 children aged between 8 and 14, $M_{age}$ = 9.99 years (*SD* = 1.54), 75% males. *DSM–5* subtype diagnoses: $N_{ADHD\text{-}I}$: 36, $N_{ADHD\text{-}C}$: 43, $N_{ADHD\text{-}H}$: 1, $N_{unclassified}$: 1. Comorbidities included: Oppositional Defiant Disorder (25%), Learning Disabilities (21%), Anxiety Disorder (10%), and Depressive Disorder (10%).<br>*Control group:*<br>63 children aged between 8 and 14, $M_{age}$ = 9.95 years (*SD* = 1.40), 87% males. 46% of the children were diagnosed with other psychiatric disorders than ADHD. Disorders: Oppositional Defiant Disorder (25%), Learning Disabilities (21%), Anxiety Disorder (10%), and Depressive Disorder (10%). | Choice Reaction task:<br>*Accuracy, Mean RTs:*<br>• ADHD group: 88.0%, 558 ms; Control group: 90.0%, 532 ms<br>*Boundary separation:*<br>• ADHD group: 1.23; Control group: 1.39<br>*Drift rate:*<br>• ADHD group: 2.00; Control group: 2.43<br>*Nondecision time (in sec):*<br>• ADHD group: 0.32; Control group: 0.31<br>Stop-Signal task:<br>*Accuracy, Mean RTs:*<br>• ADHD group: 80.0%, 602 ms; Control group: 90.0%, 605 ms<br>*Boundary separation:*<br>• ADHD group: 1.83; Control group: 2.43<br>*Drift rate:*<br>• ADHD group: 2.20; Control group: 2.53<br>*Nondecision time (in sec):*<br>• ADHD group: 0.32; Control group: 0.32<br>Note: Fast-dm software (Voss & Voss, 2007) was used to estimate the diffusion model parameters. |
| Weigard et al. (2019) | *ADHD group:*<br>209 children, $M_{age}$ = 10.20 years (*SD* = 1.31), 67% males. *DSM–IV* subtype diagnoses: $N_{ADHD\text{-}I}$: 85, $N_{ADHD\text{-}C}$: 119, $N_{ADHD\text{-}H}$: 5. Comorbidities included: Oppositional Defiant Disorder (ODD) (*N* = 82), Conduct Disorder (*N* = 15), Depressive Disorder (*N* = 9), Anxiety Disorder (*N* = 23).<br>*Control group:*<br>99 age-matched children, $M_{age}$ = 10.23 years (*SD* = 1.26), 46% males. 3 children were diagnosed with ODD. | Task summary statistics:<br>*Go mean RTs:*<br>• ADHD group: 818 ms, Control group: 771 ms<br>*Signal-respond mean RT:*<br>• ADHD group: 720 ms, Control group: 666 ms<br>*Go accuracy:*<br>• ADHD group: 0.949, Control group: 0.976<br>*Signal-respond accuracy:*<br>• ADHD group: 0.937, Control group: 0.970<br>*Mean Stop-Signal Delay (SSD, in sec):*<br>• ADHD group: 0.394, Control group: 0.454<br>*Mean Stop-signal Reaction Time (SSRT, in sec):*<br>• ADHD group: 0.424, Control group: 0.317<br>*Overall probability of "go" responses:*<br>• ADHD group: 0.577, Control group: 0.528<br>Mean ex-Gaussian race model parameters:<br>$\mu$ *(go-match, in sec):*<br>• ADHD group: 0.601, Control group: 0.594<br>$\tau$ *(go, in sec):*<br>• ADHD group: 0.228, Control group: 0.179<br>$\sigma$ *(go-match, in sec):*<br>• ADHD group: 0.125, Control group: 0.108<br>$\mu$ *(go-mismatch, in sec):*<br>• ADHD group: 1.918, Control group: 2.587<br>$\tau$ *(mean stop, in sec):*<br>• ADHD group: 0.114, Control group: 0.072<br>$\sigma$ *(go-mismatch, in sec):*<br>• ADHD group: 0.813, Control group: 0.882<br>*P (GF, on logit scale):*<br>• ADHD group: 0.047, Control group: 0.019<br>*P (TF, on logit scale):*<br>• ADHD group: 0.305, Control group: 0.134 |

(*Appendix continues*)

**Table A7** (*continued*)

| Authors | Sample characteristics | Main findings |
|---|---|---|
| Epstein et al. (2011) | *ADHD group:*<br>104 children aged between 7 and 11.<br>*DSM–IV* subtype diagnoses. Sample characteristics by subtype:<br>ADHD-I:<br>$N$ = 53, $M_{age}$ = 8.35 years, $SD$ = 1.31, 64% males. Comorbidities included: Oppositional Defiant Disorder (ODD), ($N$ = 16), Anxiety Disorder ($N$ = 20), Mood Disorder ($N$ = 1).<br>ADHD-C:<br>$N$ = 51, $M_{age}$ = 7.90 years, $SD$ = 1.11, 80% males. Comorbidities included: ODD ($N$ = 22), Conduct Disorder ($N$ = 4), Anxiety Disorder ($N$ = 18), Mood Disorder ($N$ = 1).<br>*Control group:*<br>47 children aged between 7 and 11 years, $M_{age}$ = 8.33 years ($SD$ = 1.35), 81% males. Comorbidities included: Anxiety Disorder ($N$ = 2). | Summary statistics<br>(error rates, mean RTs, Coefficient of Variation (in ms), ex-Gaussian Tau Indicator in ms):<br>• Control group: 5.3%, 528 ms, 35.43, 160.97<br>• ADHD-C group: 8.6%, 641 ms, 47.87, 243.77<br>• ADHD-I group: 9.4%, 618 ms, 44.44, 223.61<br>Note: Coefficient of Variation is calculated as follows: RT standard deviation/mean RTs. |
| Tye et al. (2016) | For all clinical groups: children underwent a clinical diagnosis based on the ICD-10 criteria (Autism (ASD), Asperger's syndrome, ADHD combined type). Afterwards, a clinical assessment was performed to specify either a pure or a comorbid research categorization.<br>*ADHD-only group:*<br>18 boys aged between 8 and 13, $M_{age}$ = 10.48 years ($SD$ = 1.91).<br>*ADHD + ASD group:*<br>29 boys aged between 8 and 13, $M_{age}$ = 10.53 years ($SD$ = 1.69).<br>The PACS criteria was used for identifying ADHD comorbid ASD.<br>*ASD-only group:*<br>19 boys aged between 8 and 13, $M_{age}$ = 11.69 years ($SD$ = 1.70).<br>The ADI-R/ADOS criteria was used for identifying ASD.<br>*Control group:*<br>26 boys aged between 8 and 13, $M_{age}$ = 10.56 years ($SD$ = 1.79). | Mean RTs, RT standard deviation, ex-Gaussian Tau Indicator across conditions:<br>(approximation from the figure)<br>*Baseline:*<br>• ADHD-only group: 950 ms, 350 ms, 320 ms<br>• ADHD + ASD group: 950 ms, 325 ms, 325 ms<br>• ASD-only group: 720 ms, 240 ms, 210 ms<br>• Control group: 780 ms, 200 ms, 160 ms<br>*Fast condition:*<br>• ADHD-only group: 600 ms, 175 ms, 170 ms<br>• ADHD + ASD group: 610 ms, 200 ms, 150 ms<br>• ASD-only group: 550 ms, 150 ms, 125 ms<br>• Control group: 550 ms, 75 ms, 100 ms |

*Note*. ADHD = attention-deficit/hyperactivity disorder; RT = reaction time; ASD = autism spectrum disorder; LBA = linear ballistic accumulator model.

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