



Minerva Access is the Institutional Repository of The University of Melbourne

Author/s:

Tiego, J;Bellgrove, MA;Whittle, S;Pantelis, C;Testa, R

Title:

Common mechanisms of executive attention underlie executive function and effortful control in children

Date:

2020-05-01

Citation:

Tiego, J., Bellgrove, M. A., Whittle, S., Pantelis, C. & Testa, R. (2020). Common mechanisms of executive attention underlie executive function and effortful control in children. *Developmental Science*, 23 (3), <https://doi.org/10.1111/desc.12918>.

Persistent Link:

<https://hdl.handle.net/11343/286938>

Article type : Paper (under 8000 words)

Common Mechanisms of Executive Attention Underlie Executive Function and Effortful Control in Children

Jeggan Tiego^{1,2}, Mark A. Bellgrove¹, Sarah Whittle^{2,3}, Christos Pantelis^{3,4},
& Renee Testa^{1,2}

¹Turner Institute for Brain and Mental Health and School of Psychological Sciences, Monash University, Australia.

²Melbourne Neuropsychiatry Centre, Department of Psychiatry, The University of Melbourne and Melbourne Health, Australia.

³Melbourne School of Psychological Sciences, The University of Melbourne, Australia.

⁴Centre for Neural Engineering, Department of Electrical and Electronic Engineering, The University of Melbourne, Australia.

Correspondence to: Jeggan Tiego, Turner Institute for Brain and Mental Health and School of Psychological Sciences, 18 Innovation Walk, Clayton Campus, Wellington Road, Monash University, VIC, 3800 Australia. Telephone +61 3 9905 3968, Facsimile +61 3 9905 3948. Email: jeggan.tiego@monash.edu

Acknowledgements

Jeggan Tiego was supported by an Australian Postgraduate Award. Mark Bellgrove was supported by ARC Future Fellowship (Level 3) (FT130101488). Sarah Whittle was supported by NHMRC Career Development Fellowship (1125504). Christos Pantelis was supported by

This is the author manuscript accepted for publication and has undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the [Version of Record](#). Please cite this article as [doi: 10.1111/DESC.12918](https://doi.org/10.1111/DESC.12918)

This article is protected by copyright. All rights reserved

NHMRC Senior Principal Research Fellowship (628386 & 1105825). Conflicts of interest: none. We wish to thank the Department of Education and Early Childhood Development, Catholic Education Commission Archdiocese of Melbourne, and Independent Schools of Victoria for their consent to conduct research in their schools. We also thank all the schools, parents, and students that participated in the research.

Abstract word count: 250

Number of tables: 4

Number of figures: 9

Word Count: 10,433

RESEARCH HIGHLIGHTS

- Behavioral ratings of executive function and effortful control measured the same self-regulation construct in children aged 11 and 12 years
- Cognitive tasks assessing working memory capacity, response inhibition, and general intelligence measured a common executive attention factor
- The executive attention factor explained 30% of the variance in self-regulation as measured by behavioral ratings of executive function and effortful control
- Task-based cognitive assessment failed to explain statistically significant additional variance in attention deficit hyperactivity disorder problems to that accounted for by behavioral ratings of self-regulation

ABSTRACT

Executive Function (EF) and Effortful Control (EC) have traditionally been viewed as distinct constructs related to cognition and temperament during development. More recently, EF and EC have both been implicated in top-down self-regulation - the goal-directed control of cognition, emotion, and behavior. We propose that executive attention, a limited-capacity

attentional resource subserving goal-directed cognition and behavior, is the common cognitive mechanism underlying the self-regulatory capacities captured by EF and EC. We addressed three related questions: 1) Do behavioral ratings of EF and EC represent the same self-regulation construct? 2) Is this self-regulation construct explained by a common executive attention factor as measured by performance on cognitive tasks? and 3) Does the executive attention factor explain additional variance in attention deficit hyperactivity disorder (ADHD) problems to behavioral ratings of self-regulation? Measures of performance on complex memory span, general intelligence, and response inhibition tasks were obtained from 136 preadolescent children ($M = 11$ years, 10 months, $SD = 8$ months), along with self- and parent-reported EC, and parent-reported EF, and ADHD problems. Results from structural equation modeling demonstrated that behavioral ratings of EF and EC measured the same self-regulation construct. Cognitive tasks measured a common executive attention factor that significantly explained 30% of the variance in behavioral ratings of self-regulation. Executive attention failed to significantly explain additional variance in ADHD problems beyond that explained by behavioral ratings of self-regulation. These findings raise questions about the utility of task-based cognitive measures in research and clinical assessment of self-regulation and psychopathology in developmental samples.

Keywords: executive function; effortful control; executive attention; self-regulation; ADHD; developmental psychopathology.

Executive Function (EF) and Effortful Control (EC) are constructs related to top-down self-regulation in children and adolescents - the ability to control cognition, emotion, and behavior in a goal-directed manner (Nigg, 2017; Zhou, Chen, & Main, 2012). EF is an umbrella term encompassing a range of cognitive processes involved in goal-directed, context-appropriate behavior, particularly in conditions characterized by novelty and interference from distracting information (Banich, 2009; Diamond, 2013). EC is a dimension of temperament related to individual differences in children's and adolescents' ability to control their attention and behavior (Derryberry & Rothbart, 1988; Rothbart & Gartstein, 2008). Some researchers have contended that EF and EC are overlapping constructs (Bridgett, Oddi, Laake, Murdock, & Bachmann, 2013; Holzman & Bridgett, 2017; Nigg, 2017; Zhou et al., 2012). Others have argued they are conceptually and empirically distinct and are differentially related to developmental psychopathology, such as attention deficit hyperactivity disorder (ADHD) (Eisenberg, 2017; Samyn, Roeyers, Bijttebier, Rosseel, &

Wiersema, 2015). Here, we propose that *executive attention* - a limited-capacity attentional resource subserving the goal-directed control of cognition and behavior - is the common cognitive mechanism underlying EF and EC and can explain their conceptual and empirical overlap.

1.1 Executive Attention and the Attention Networks Model

Research on developmental self-regulation has been strongly influenced by the attention networks model (Posner & Petersen, 1990; Rueda, Posner, & Rothbart, 2011). Within this model, attention is conceptualized as several interrelated and mutually supportive processes subserved by neuroanatomically distinct functional networks (Petersen & Posner, 2012; Rueda, Pozuelos, & Combata, 2015). Among these, the ‘executive control of attention’ (also ‘executive control’ or ‘executive attention’) network is specialized for detecting and resolving conflict between competing processes (Fan, Raz, & Posner, 2003; Petersen & Posner, 2012). The executive attention network is particularly relevant to the goal-directed control of attention and behavior in contexts of novelty and interference (Petersen & Posner, 2012; Posner & Rothbart, 2009). For this reason, the executive attention network has been implicated as the neurobiological basis of top-down self-regulation and argued to play an important role in self-regulation during development (Rothbart, Sheese, & Posner, 2007; Rueda, Posner, & Rothbart, 2005).

According to Posner and colleagues, individual differences in the efficiency of the executive attention network can be measured using stimulus-response compatibility tasks, such as the Stroop, Eriksen flanker (‘flanker’), and Simon tasks, and the attention networks test (Fan, McCandliss, Sommer, Raz, & Posner, 2002; Petersen & Posner, 2012; Simonds, Kieras, Rueda, & Rothbart, 2007). Stimulus-response compatibility tasks consist of two main conditions: 1) congruent (or compatible), in which there is a correspondence between task-relevant and task-irrelevant stimuli and response elements; and 2) incongruent (or incompatible), in which there is conflict between task-relevant stimuli and task-irrelevant distractors that prime an automatic, but incorrect, response (Eriksen, 1995; Kornblum, Hasbroucq, & Osman, 1990; Lu & Proctor, 1995; MacLeod, 1991). The mean reaction time difference between incongruent and congruent trials has been called the ‘interference effect’, ‘conflict effect’, or ‘conflict score’. It is used as an index of the efficiency of the executive attention network in resolving conflict between competing stimuli and response alternatives during task performance on incongruent trials (Rueda et al., 2011; Rueda et al., 2015). From the perspective of the attention networks model, executive attention therefore refers to the

ability to detect and resolve conflict (Petersen & Posner, 2012; Posner & Rothbart, 2009). An implicit assumption of unidimensionality is revealed by the use of a single interference effect obtained from stimulus-response compatibility tasks as a measure of executive attention (Posner et al., 2002; Rueda et al., 2015).

1.2 Effortful Control Reflects Efficiency of the Executive Attention Network

Effortful Control (EC) represents the self-regulatory aspect of temperament identified in the psychobiological model first proposed by Rothbart and Derryberry (1981) (Rothbart & Bates, 2006; Rothbart & Gartstein, 2008). It reflects a range of self-regulatory capacities that are seen to first emerge in early infancy and demonstrate rapid development throughout childhood and adolescence, reflecting maturation of the neural networks underlying the voluntary control of attention and behaviour (Rothbart, Ellis, Rueda, & Posner, 2003; Rothbart & Gartstein, 2008; Rueda et al., 2005). In the psychobiological model of temperament, EC is defined as “...*the efficiency of executive attention – including the ability to inhibit a dominant response and/or activate a subdominant response, to plan, and to detect errors.*” (Rothbart & Bates, 2006, p.129). Temperament researchers therefore equate EC with individual differences in the efficiency with which executive attention supports self-regulation (Rueda et al., 2011). Thus, the interference effect on stimulus-response compatibility tasks has been used as a measure of EC in developmental samples (Rueda, Posner, & Rothbart, 2004; Simonds et al., 2007).

1.3 Executive Attention as Working Memory Capacity

Executive attention is also conceptualized and measured with respect to working memory capacity (WMC) (Engle, 2002; Kane, Bleckley, Conway, & Engle, 2001). WMC is situated within broader theoretical models of working memory, a limited capacity cognitive system that functions to maintain and manipulate information over brief periods of time (Baddeley, 2012). In the multi-component model, originally described by Baddeley and Hitch (1974), the ‘*Central Executive*’ is a domain-general attentional resource that regulates the function and contents of two modality-specific temporary storage systems subserving auditory-verbal and visuospatial short-term memory (Baddeley, 2003, 2012). WMC largely corresponds with the Central Executive as conceptualized in the multi-component model of working memory (Hofmann, Friese, Schmeichel, & Baddeley, 2011; Repovs & Baddeley, 2006). Studies suggest that this ‘executive’ or ‘attention control’ component of working memory accounts for a large proportion of the variance in WMC, with residual variance

attributable to individual differences in short-term storage capacity and the efficiency of secondary retrieval mechanisms (Shipstead, Lindsey, Marshall, & Engle, 2014; Unsworth & Spillers, 2010).

WMC is often assessed using complex span tasks, which measure retention of a series of presented items interleaved with a distracting secondary processing task (Conway et al., 2005). According to the executive attention perspective of WMC developed by Kane, Engle and colleagues, goal-relevant information is actively maintained through mechanisms of executive attention, which keep the contents of working memory in a readily accessible state and protects it from interference and temporal decay (Kane, Conway, Hambrick, & Engle, 2007). The ability to actively maintain goal-relevant information, such as stimulus-response associations and task rules, is believed to enable individuals to override automatic processing and engage in goal-directed cognition and behavior (Engle, 2002; Kane & Engle, 2002). For this reason, WMC has been implicated as an important mechanism in top-down self-regulation (Hofmann et al., 2011; Ilkowska & Engle, 2010). Studies in children and adults have demonstrated that individuals with higher WMC are better able to delay gratification, as well as more effectively regulate the experience and expression of emotion (Hofmann, Gschwendner, Friese, Wiers, & Schmitt, 2008; Schmeichel, Volokhov, & Demaree, 2008; Yu, Kam, & Lee, 2016).

1.4 Executive Attention is the Goal Maintenance Mechanism Underlying Common EF in the Unity/Diversity Model

In the developmental literature, executive functions (EF) have been described as a family of distinct, but functionally-related, goal-directed control mechanisms that act to initiate, maintain, and coordinate lower-level cognitive processes (Diamond, 2013; Nigg, 2017). Working memory and response inhibition are two key cognitive processes commonly subsumed under the EF rubric and represented across different theories and models (Diamond, 2013; Nigg, 2017). Shifting between alternative stimulus-response associations and/or attentional sets (also ‘task-set switching’ or ‘cognitive flexibility’) is another core EF that is later-developing and partially dependent upon inhibition and working memory (Best & Miller, 2010; Diamond, 2013). Together, these ‘first-order’ EFs are believed to support more complex ‘second-order’ EFs, such as planning, organization, problem solving, reasoning, and decision-making (Best & Miller, 2010; Diamond, 2013).

One of the more prominent accounts of EF in the literature is the Unity/Diversity model of Miyake and colleagues (Miyake et al., 2000). The model includes three first-order EFs measured at the level of latent variables using structural equation modeling: 1) shifting between tasks or mental sets ('Shifting'); 2) updating and monitoring of working memory representations ('Updating'); 3) inhibition of dominant or prepotent responses ('Inhibiting') (Miyake et al., 2000). When analyzed as a direct hierarchical factor model these EFs exhibit both 'unity' and 'diversity' (Miyake & Friedman, 2012). More specifically, the Shifting and Updating factors are associated with distinct, ability-specific variance, but these three EFs also exhibit strong empirical overlap captured by a general factor that completely subsumes variance in the Inhibiting factor (Friedman, Miyake, Robinson, & Hewitt, 2011; Friedman et al., 2008). This general factor has been termed '*Common EF*' and may reflect a shared reliance of EFs on goal maintenance processes for top-down control (Miyake & Friedman, 2012). The proposed cognitive mechanisms underlying Common EF are strikingly similar to the executive attention account of WMC (Kane et al., 2007). In fact, Friedman and Miyake (2017) draw strong parallels between the two, concluding that the same goal-maintenance mechanisms underlie Common EF and the executive attention component of WMC. Several studies have already demonstrated a close empirical association between two key EFs, Inhibiting (i.e. response inhibition) and Updating, and WMC (Schmiedek, Hildebrandt, Lövdén, Wilhelm, & Lindenberger, 2009; Shipstead et al., 2014; Wilhelm, Hildebrandt, & Oberauer, 2013).

1.5 Executive Attention: A Common Construct in the Attention Networks Model and Executive Attention Account of WMC

Individual differences in the executive attention component of WMC are most relevant in contexts of strong interference and automatic response tendencies, such as those comprising stimulus-response compatibility and response inhibition tasks (Kane et al., 2001; Kane & Engle, 2002). Consistent with this perspective, higher WMC predicts lower interference effects on tasks used to measure executive attention and EC within the attention networks model, including the attention networks test, Stroop, and flanker tasks (Heitz & Engle, 2007; Kane & Engle, 2003; Redick & Engle, 2006). WMC is associated with better selective visual attention, facilitating the ability to focus on task-relevant targets and filter out task-irrelevant distracters (Awh, Jonides, & Reuter-Lorenz, 1998; Burnham, Sabia, & Langan, 2014; Downing, 2000). Higher WMC also predicts better inhibitory control on measures of response inhibition, including the stop signal, go/no-go, and anti-saccade tasks

(Kane et al., 2001; Tiego, Testa, Bellgrove, Pantelis, & Whittle, 2018; Unsworth, Schrock, & Engle, 2004). Selective visual attention and response inhibition are abilities ascribed to executive attention in the attention networks model, as well as being subsumed under EC, suggesting strong convergence on a common cognitive construct (Eisenberg, Hofer, & Vaughan, 2007; Rueda et al., 2005).

It has been suggested that the executive attention component of WMC reflects a domain general attentional resource for actively maintaining goal-relevant neural representations (e.g., motivational context, task rules, stimulus–response associations, object features / attribute) as an ‘attentional set’ or ‘attentional template’ that biases lower-level perceptual, cognitive, and behavioral processes through top-down control (Corbetta & Shulman, 2002; Desimone & Duncan, 1995; Kane & Engle, 2002). This theory provides a parsimonious account of executive attention, as the mechanisms supporting goal-directed cognition and behavior in novel contexts and interference-rich environments, such as those encountered during performance of stimulus-response compatibility and response inhibition tasks, tests of EF, and general intelligence tasks (Brydges, Reid, Fox, & Anderson, 2012; Engel de Abreu, Conway, & Gathercole, 2010; Kane & Engle, 2002; McCabe, Roediger, McDaniel, Balota, & Hambrick, 2010). Posner, Rothbart and colleagues have further acknowledged that the executive component of WMC and executive attention within the attention networks model are synonymous (Rueda et al., 2011).

Recent accounts posit dissociable mechanisms of maintenance and disengagement comprising the executive attention construct (Engle, 2018; Shipstead, Harrison, & Engle, 2016). Researchers suggest these cognitive mechanisms account for the observed strong associations between measures of WMC and general intelligence (Burgoyne, Hambrick, & Altmann, 2019; Engle, 2018). Psychometric *g*, a factor that captures shared variance in performance across tests of general intelligence, is correlated at or near unity with WMC, reflecting a common reliance on executive attention (Barbey et al., 2012; Brydges et al., 2012; Conway, Kane, & Engle, 2003; Engel de Abreu et al., 2010; Jensen, 2002; Nisbett et al., 2012). Engle (2018) posits that complex span tasks primarily measure the capacity to maintain information, whereas tests of general intelligence tap the ability to disengage from previously encountered, but no longer relevant, information. However, tasks measuring WMC and general intelligence are highly correlated because both require the controlled engagement and disengagement of focal attention (Burgoyne et al., 2019; Engle, 2018;

Shipstead et al., 2016). From this perspective, the executive attention construct reflects cognitive mechanisms of maintenance and disengagement that function in combination to focus attention on relevant information (Shipstead et al., 2016).

1.6 Performance on Cognitive Tasks versus Behavioural Ratings as Measures of Self-Regulation in Relation to Developmental Psychopathology

Despite the apparent convergence of EF and EC (Holzman & Bridgett, 2017; Nigg, 2017; Zhou et al., 2012), some theorists contend they are conceptually and empirically distinct (Eisenberg, 2017; Samyn et al., 2015). Unfortunately, there is a paucity of empirical studies that have directly tested the overlap between EC and EF (Bridgett et al., 2013; Lin, Liew, & Perez, 2019; Samyn et al., 2015). Existing conceptual and empirical dissociations between EF and EC, particularly as predictors of developmental psychopathology, may reflect differences in measurement approach rather than fundamental differences between these constructs (Bridgett et al., 2013; Samyn et al., 2015; Toplak, West, & Stanovich, 2013). EF has traditionally been measured using performance on cognitive tasks, whereas EC has been largely measured using behavioral ratings based on parent- and self-report (Zhou et al., 2012). However, EF in developmental samples is increasingly being assessed using behavioral rating measures based on parent- and/or self-report, such as the Behavior Rating Inventory of Executive Function (BRIEF) (Gioia, Isquith, Guy, & Kenworthy, 2000). The BRIEF assesses EF using eight clinical scales: working memory, inhibit, shift, emotional control, monitor, planning/organization, initiate, and organization of materials, that can be summed to form two index scores – the metacognition index and behavioral regulation index (Gioia et al., 2000). Several of these self-regulatory capacities converge with those incorporated by definitions of EC, including the ability to focus and ‘shift’ attention, ‘inhibit’ dominant responses, ‘plan’, detect errors (i.e. monitor), and modulate emotional responses (i.e. emotional control) (Eisenberg et al., 2007; Rothbart & Bates, 2006). These self-regulatory abilities are also assessed using questionnaires designed to measure EC (Putnam, Ellis, & Rothbart, 2001).

Conversely, EC has been increasingly measured using performance on cognitive tasks. The Stroop, flanker, Simon, stop signal, and go/no-go tasks, have been used interchangeably as measures of EC, EF, and executive attention (Allan & Lonigan, 2011; Banich, 2009; Diamond, 2013; Fan, Flombaum, McCandliss, Thomas, & Posner, 2003; Fan et al., 2002; Kochanska, Murray, & Harlan, 2000; Miyake & Friedman, 2012; Murray &

Kochanska, 2002). EF and EC are thus likely closely associated constructs when both measured using behavioral ratings or performance-based tasks (Bridgett, Oddi, Laake, Murdock, & Bachmann, 2013; Lin et al., 2019). For example, Lin et al. (2019) found that EF and EC could not be empirically differentiated using laboratory-based tasks in a sample of 244 children aged 4 – 6 years. This also suggests that commonality in behavioral ratings of EF and EC is explained by task-based cognitive measures of executive attention and that these measurement approaches should converge on a common self-regulation construct (Nigg, 2017; Zhou et al., 2012). However, performance on cognitive tasks has typically exhibited weak to modest correlations with behavioral ratings of EF and EC (Rueda, Posner, et al., 2004; Samyn et al., 2015; Simonds et al., 2007; Ten Eycke & Dewey, 2016; Toplak, Bucciarelli, Jain, & Tannock, 2008). A lack of convergence between task-based and self-report measures is a problem encountered in the self-regulation research literature more broadly and has been attributed to the poor psychometric properties of task-based measures, as well as their inability to reliably measure individual differences (Enkavi et al., 2019; Hedge, Powell, & Sumner, 2017).

Toplak et al. (2013) conducted a review of the EF research literature and concluded that cognitive tasks and behavioral ratings measure different constructs (see also Ten Eycke & Dewey, 2016). Additionally, behavioral ratings of EF and EC are more strongly predictive of developmental psychopathology, such as ADHD, than performance on cognitive tasks (Muris, van der Pennen, Sigmond, & Mayer, 2008; Samyn et al., 2015; Toplak et al., 2008; Toplak et al., 2013). Toplak et al. (2013) suggested that cognitive tasks measure ‘optimal’ levels of performance in controlled conditions, whereas behavioral ratings are more representative of ‘typical’ performance in ecologically valid contexts, arguably more relevant to everyday self-regulation and developmental psychopathology. From this perspective, it was concluded that cognitive tasks and behavioral ratings of self-regulation explain unique variance in symptoms of developmental psychopathology, particularly ADHD (Toplak et al., 2013).

1.7 Limitations of Previous Studies

Conceptual and methodological limitations of previous studies may explain the poor association between performance on cognitive tasks and behavioral rating measures of self-regulation and developmental psychopathology. First, several of the scales on the BRIEF, the most widely used behavioral rating measure of EF in developmental samples, have no

parallel cognitive tasks, making empirical relationships between these two measurement approaches less likely (Toplak et al., 2013). Confirmatory factor analysis (CFA) has indicated that behavioral rating data obtained from the BRIEF coalesces around three higher-order factors, metacognition, emotional regulation, and behavioral regulation, rather than reflecting the eight clinical scales or the metacognition index and behavioral regulation index (Egeland & Fallmyr, 2010; Fournet et al., 2015; Gioia, Isquith, Retzlaff, & Espy, 2002; Little et al., 2017). Similarly, EC was originally believed to consist of three distinct, but interrelated, abilities as measured by separate subscales: 1) *Attentional Control* - the ability to voluntarily focus and shift attention, as well as disengage from alternative sources of attention using cognitive distraction; 2) *Inhibitory Control* - the ability to inhibit contextually inappropriate behavioral responses; and 3) *Activation Control* - the capacity to undertake an action when there is a strong tendency to avoid it (Eisenberg, Smith, Sadovsky, & Spinrad, 2004; Putnam et al., 2001). However, more recent work suggests these three abilities largely reflect a ‘*Common EC*’ construct, conceptually similar to the Common EF factor in the Unity/Diversity model (Snyder, Gulley, et al., 2015). Parcelling item-level data by using questionnaire subscale or total scores without regard to the underlying factor structure can result in parameter bias and model misspecification (Bandalos, 2002; Marsh, Lüdtke, Nagengast, Morin, & Von Davier, 2013). This may explain weaker than expected convergence between these constructs in previous studies, which have not taken into account the latent structure of behavioral ratings of EF and EC using analysis of behavioural ratings at an item-level (e.g. Bridgett et al., 2013).

Second, the cognitive tasks used to measure EF and executive attention are often characterized by poor reliability, which constrains the strength of the empirical associations that can be measured with other variables (Ghiselli, Campbell, & Zedeck, 1981; Hedge et al., 2017). Third, EF tasks are affected by task impurity: individual differences in task performance combines variance from multiple sources beyond the function of interest, including non-target cognitive processes, task-specific variance, and measurement error (Enkavi et al., 2019; Snyder, Miyake, & Hankin, 2015). Fourth, executive attention has been narrowly defined in the developmental literature (Diamond, 2013) and measured using single tasks in previous studies (e.g. Rueda et al., 2004; Simonds et al., 2007), resulting in poor construct representation (Strauss & Smith, 2009). Further, ADHD symptoms and other measures of developmental psychopathology are often obtained through parent-report. The stronger relationship between measures of developmental psychopathology and behavioral

ratings compared to performance on cognitive tasks may be attributable to common method variance and informant bias (Bridgett et al., 2013; Podsakoff, MacKenzie, & Podsakoff, 2012; Toplak et al., 2013). Given these obstacles, identifying statistically significant and meaningful associations between performance on cognitive tasks and behavioral ratings of EF, EC, and developmental psychopathology is challenging (Anderson, Anderson, Northam, Jacobs, & Mikiewicz, 2002; Mahone et al., 2002; Toplak et al., 2008).

1.8 Current Study

We aimed to investigate the relationships between behavioural ratings of EF and EC, performance on cognitive task measures of executive attention, and problems associated with developmental psychopathology. We addressed several limitations of previous studies. First, we used CFA to model the optimal latent structure of the BRIEF and EATQ-R to obtain a more accurate estimate of their empirical association. Second, we included both parent- and self-reported EC to account for informant bias in estimating the relationship between behavioral ratings of EC, EF, and developmental psychopathology. Third, we used multiple cognitive tasks, including tests of WMC, response inhibition, and general intelligence, in combination with structural equation modeling (SEM) to measure a common executive attention factor. Use of these multiple measures enabled us to capture a range of cognitive processes ascribed to the executive attention construct, including maintenance, attentional disengagement, and voluntary control of behavior (Kane et al., 2001; Kane & Engle, 2002; Shipstead et al., 2016). Fourth, we used SEM to examine the inter-relationships between executive attention, behavioral ratings of EF and EC, and parent-reported ADHD problems. Using SEM allowed us to obtain less biased estimates of the hypothesised empirical relationships between executive attention, EF, EC, and ADHD problems by reducing the effect of measurement error and by modeling the optimal latent structure of the constructs of interest.

ADHD is a neurodevelopmental disorder characterized by at least two, major symptom dimensions: 1) inattention / disorganization, and 2) hyperactive / impulsive (APA, 2013; Frick & Nigg, 2012; Hinshaw, 2018). We chose to examine ADHD problems because this disorder is an archetypal model of self-regulatory failure linked to EF deficits, particularly working memory and response inhibition (Barkley, 2014; Lipszyc & Schachar, 2010; Oosterlaan & Sergeant, 1996). We adopted a dimensional approach by measuring ADHD on a continuum in a non-selected, community sample using the Child Behavior

Checklist (CBCL) (Achenbach & Rescorla, 2001; Achenbach, 2009). Dimensional approaches have long been advocated in developmental psychopathology and are now widely adopted in psychopathology research (Cuthbert, 2014; Hudziak, Achenbach, Althoff, & Pine, 2007; Krueger et al., 2018). According to dimensional conceptualizations, ADHD is a spectrum disorder with symptoms occurring along a continuum of severity that can be quantified in the broader developmental population (Coghill & Sonuga-Barke, 2012; Frick & Nigg, 2012; Hinshaw, 2018). Diagnostic criteria and clinical significance represent arbitrary thresholds along this continuum (Frick & Nigg, 2012). A dimensional approach to measuring ADHD problems is preferable to traditional categorical models in the current research context, because it leverages symptom variation across the full spectrum of severity, increasing variance and statistical power for examining the association with executive attention, EF, and EC (Helzer, Kraemer, & Krueger, 2006; Kraemer, Noda, & O'Hara, 2004).

We addressed the following three questions: 1) Do behavioral ratings of EF and EC measure the same self-regulation construct? 2) Is the commonality between behavioral ratings of EF and EC explained by a unitary executive attention factor? and 3) Do task-based measures of executive attention and behavioral ratings of EF and EC predict unique or overlapping variance in ADHD problems? We hypothesized that behavioral rating measures of EC and EF would be strongly empirically-related and converge on a common self-regulation construct. Second, we predicted that an executive attention factor, as measured by performance on cognitive tasks, would significantly explain substantial variance in the self-regulation construct measured by behavioral ratings of EF and EC. Finally, we expected that executive attention, as measured by performance on cognitive tasks, would predict unique variance in the severity of parent-reported ADHD problems in addition to that explained by behavioral ratings of EF and EC.

2. METHODS

2.1 Participants

The sample comprised 136 (125 right-handed) typically-developing, pre-adolescent children (86 males, 50 females), aged 11 years, 0 months to 12 years, 11 months ($M = 11$ years, 10 months, $SD = 8$ months), with no history of diagnosed neurological or psychiatric disorders. Participants were recruited from 52 Government (63.8%), Catholic (30.8%), and Independent (5.4%) primary and secondary schools located in metropolitan Melbourne, Australia using advertisement flyers handed out to students and through school newsletters.

The majority (86%) of the student sample were of European descent. Sample size selection was based roughly on a recommended minimum case to parameter ratio ($N:q$) of 10:1 for the structural regression models (Jackson, 2003; Kline, 2015). Ethics approval for the research project and associated methodology was obtained from the Monash University Human Research Ethics Committee (Approval Number: CF13/1307 - 2013000673). The primary caregivers of participants provided written informed consent in accordance with the Declaration of Helsinki and informed written assent to participate was obtained from the research participants.

2.2 Materials

2.2.1 Cognitive task measures of executive attention.

2.2.1.1 Working memory capacity.

WMC was measured using the three verbal working memory subtests of the automated working memory assessment (AWMA): 1) listening recall; 2) counting recall; and 3) backward digit recall (Alloway, 2007). The AWMA was administered on a Dell Inspiron 1520 computer with 33 cm screen at 1280 x 800 resolution using the Windows Vista operating system and operated by one of the investigators. Details of task administration have been provided elsewhere (Tiego et al., 2018) and are also provided in supporting information. The dependent variables were the subtest raw scores reflecting the number of correctly answered trials.

2.2.1.2 Response inhibition.

Response inhibition was measured using three tasks: 1) stop signal; 2) go/no-go; and 3) Simon tasks. The stop signal task was administered using the ‘stop-it’ and ‘analyze-it’ program (Verbruggen, Logan, & Stevens, 2008) installed on a Dell Latitude D420 Laptop computer running Windows XP. The dependent variable was stop signal reaction time (SSRT) calculated using the subtraction method (Logan, Schachar, & Tannock, 1997; Verbruggen et al., 2008). The go/no-go (Menon, Adleman, White, Glover, & Reiss, 2001) and Simon (Sparkes, 2006) tasks were programmed using PsychoPy V1.80.03 (Peirce, 2007, 2008) and administered on the same computer as the AWMA. Dependent variables were the number of commission errors on no-go trials and Simon stimulus-response (SR-) conflict (i.e. mean reaction time difference between incongruent & control trials), respectively. See supporting information and Tiego et al. (2018).

2.2.1.3 General intelligence.

Tests of general intelligence were used as additional measures of the maintenance and disengagement mechanisms of the executive attention construct (Engle, 2018; Shipstead et al., 2016). General intelligence was measured using a short form of the Australian Standardized Edition of the Wechsler Intelligence Scale for Children – Fourth Edition (WISC-IV) (Wechsler, 2003a) consisting of three core subtests – 1) vocabulary; 2) matrix reasoning; and 3) symbol search. These subtests were chosen because vocabulary and matrix reasoning have amongst the strongest loadings on psychometric g (Flanagan & Kaufman, 2004; Wechsler, 2003b) and in combination, these three subtests have a high validity coefficient ($r = .92$) with full-scale intelligence (Sattler, 2008; Tellegen & Briggs, 1967). The dependent variables were the subtest raw scores reflecting the number of correctly answered items.

2.2.2 Behavioral ratings of EC, EF, and ADHD.

2.2.2.1 The early adolescent temperament questionnaire – revised self- and parent-report forms.

The early adolescent temperament questionnaire-revised (EATQ-R) self-report (65-item) and parent-report (62-item) forms are questionnaires that assess temperament in children and adolescents aged 9 to 16 years (Ellis & Rothbart, 2001). Each questionnaire item is a statement made about a typical cognitive, emotional, or behavioral response to a situation. Respondents endorse the extent to which they agree with each item on a 5-point Likert scale ($1 = \textit{Almost always untrue}$ to $5 = \textit{Almost always true}$). These questionnaires measure EC, as well as the two reactive domains of temperament, negative affectivity and positive affectivity (Putnam et al., 2001). The dependent variables used in the current study were the total raw scores obtained on the self-report and parent-report EC scales, as revealed by CFA (see 3.1 CFA Models). The eight and nine reverse-scored EC items of the self- and parent-report EATQ-R were recoded prior to analyses.

2.2.2.2 Behavior rating inventory of executive function (BRIEF) – parent-report form.

The BRIEF parent-report form is a questionnaire designed for completion by primary caregivers for assessing EF in children and adolescents aged 5 to 18 years (Gioia et al., 2000). Each item consists of a statement relating to specific behaviors and respondents endorse the frequency with which the behavior has occurred over the past six months [i.e. $N = \textit{Never}$ (1), $S = \textit{Sometimes}$ (2), $O = \textit{Often}$ (3)]. Responses are summed and averaged to

yield scores for eight clinical scales that represent the level of functioning in each domain: inhibit, shift, emotional control, initiate, working memory, plan/organize, organization of materials, and monitor. Higher scores represent more problems with EF. The BRIEF is a validated assessment tool that is used widely in clinical and research contexts (Fitzpatrick & Schraw, 2003; Gioia et al., 2002). The dependent variables used were the total raw scores obtained on the clinical scales and then composite raw scores for the derived ‘metacognition’ and ‘emotional and behavioral regulation’ constructs as revealed by CFA (see 3.1 CFA Models).

2.2.2.3 Child behavior checklist/6 – 18.

The child behavior checklist/6 – 18 (CBCL) is a parent-report form that asks primary caregivers about the presence and extent of emotional and behavioral problems exhibited by their child aged 6 to 18 years over the past six months (Achenbach & Rescorla, 2001). The form consists of 113 items in the form of statements related to the presence of problem behaviors. Respondents endorse each item with respect to the presence and extent of each symptom on a 3-point Likert scale ($0 = \text{Not True}$, $1 = \text{Somewhat or Sometimes True}$, $2 = \text{Very True or Often True}$). The dependent variable was the summed raw score obtained for each participant on the 7-item DSM-orientated ADHD problems scale, which includes problems corresponding to diagnostic criteria for ADHD in the Diagnostic and Statistical Manual of Mental Disorders – Fourth Edition (DSM-IV) (Achenbach & Rescorla, 2001; APA, 2000). Cut-off T scores provide a criterion for evaluating the severity and clinical significance of emotional and behavioral problems.

2.3 General Procedure

Details of the general testing procedures used for data collection have been previously described (Tiego et al., 2018) and are also provided in supporting information.

2.4 Statistical Procedures

Analysis of missing values, normality, and outliers are described in supporting information. All models were estimated in Mplus 7.2 using the covariance matrix (Muthén & Muthén, 1998 - 2012). CFA models of the ordered categorical data obtained from the EATQ-R self- and parent-report forms were estimated using the weighted least squares means and variance (WLSMV) adjusted estimator (Muthén, du Toit, & Spisic, 1997). All other CFA and structural regression models were estimated using full information maximum likelihood with the expectation maximization algorithm to account for missing data (Enders, 2010). All

models were estimated with non-target indicator cross-loadings and error covariances initially constrained to zero (Byrne, 2012; Hair, Black, Babin, & Anderson, 2010). *Post hoc* model fitting was performed by freeing theoretically plausible error covariances for estimation one at a time with reference to modification indices and with adjustment of significance thresholds for multiple comparisons using the Benjamini-Hochberg false discovery rate (B-H FDR; $q = .05$) (Benjamini & Hochberg, 1995; Cribbie, 2007).

Global model fit was assessed using a combination of fit indices (Byrne, 2012; Hair et al., 2010). The χ^2 test statistic is the gold standard metric for evaluating overall model fit and was referred to first (Hayduk, Cummings, Boadu, Pazderka-Robinson, & Boulianne, 2007; Marsh, Hau, & Wen, 2004). A probability value $> .05$ indicates that the null hypothesis of exact fit of the model reproduced covariance matrix to the observed covariance matrix cannot be rejected (Kline, 2015). Approximate fit indices perform poorly in small samples sizes with few degrees of freedom (e.g. Kenny, Kaniskan, & McCoach, 2015; Taasoobshirazi & Wang, 2016). Furthermore, there are no accepted thresholds for evaluating overall model fit based on approximate fit indices (Barrett, 2007; Hayduk et al., 2007; Kline, 2015). Nevertheless, we report the root mean square error of approximation (RMSEA) and associated 90% confidence interval (*CI*), which provides a means of evaluating the error of approximation that incorporates increased sampling error associated with small samples (MacCallum, Browne, & Sugawara, 1996). In addition, the comparative fit index (CFI), and standardized root mean square residual (SRMR), or weighted root mean residual (WRMR) for ordered categorical data, are also reported with a higher CFI and lower SRMR or WRMR indicating better model fit (Byrne, 2012; Hair et al., 2010). We evaluated local model fit and report standardized covariance residuals exceeding the critical threshold ($Z > \pm 1.96$, $p < .05$) as a more sensitive indication of model misspecification (Kline, 2015).

To facilitate adjudication between competing models with close comparative fit based on maximum likelihood estimation, we report the Bayesian Information Criterion (BIC), Bayesian conditional posterior probability [$\Pr_{\text{BIC}}(H_i|D)$], and Bayes Factors (*BF*) (Wagenmakers, 2007). The conditional posterior probability quantifies the relative probability ($p \sim .00 - 1.0$) that a given model provides the best fit to the observed data compared to competing models. The Bayes Factor directly compares the likelihood of two competing models in terms of a ratio (Jarosz & Wiley, 2014). We also provide model diagnostics, unidimensionality statistics, and model-based reliability estimates based on the

bifactor models of the EATQ-R to adjudicate between a unidimensional model and alternative multi-factorial models of EC (Reise, 2012; Reise, Scheines, Widaman, & Haviland, 2013; Rodriguez, Reise, & Haviland, 2016). The best-fitting models were selected according to global fit statistics, local fit testing, and model parsimony (i.e. the model with the fewest factors).

We used a jigsaw piece modeling strategy in combination with factor score regression, single-indicator latent variables, and bootstrapped standard errors to circumvent issues related to small sample size, multivariate non-normality, and model complexity (Bollen, 2000; Devlieger & Rosseel, 2017; Enders, 2010; Hayduk & Littvay, 2012). Briefly, we first estimated the best-fitting measurement model for each construct (i.e. executive attention, EF, & EC) prior to combining them in the final structural regression model, enabling us to conserve the number of free parameters (i.e. degrees of freedom [df]) and a higher participant to parameter ratio ($N:q$) (Bollen, 2000; Kline, 2015). Factor score estimates were generated using the regression method for the executive attention construct based on CFA of the nine performance-based tasks (DiStefano, Zhu, & Mindrila, 2009; Grice, 2001; Muthén & Muthén, 1998 - 2012). This eliminated the need to include the full measurement model of executive attention and therefore conserved free parameters and statistical power. The factor score regression method results in unbiased parameter estimates in structural regression models when the factor score estimates are generated using the regression method and are used as an exogenous (i.e. independent) latent variable (Devlieger, Mayer, & Rosseel, 2016; Devlieger & Rosseel, 2017; Skrondal & Laake, 2001).

The executive attention factor score estimates were entered in the structural regression models as a single-indicator latent variable with error variance fixed to reflect the inverse of the factor determinacy $[(1 - \rho) \cdot \sigma^2]$, which represents a validity coefficient (Grice, 2001). ADHD problems was specified as a single-indicator latent variable with error variance of the summed raw scale score fixed to reflect the inverse of Cronbach's alpha internal consistency reliability estimate $[(\epsilon = (1 - \alpha) \cdot \sigma^2)]$ (Bollen, 1989). Use of single-indicator latent variables reduces unnecessary model complexity and identification problems and facilitates a greater focus on the hypothesized statistical dependence relationships (i.e. regression coefficients) between the constructs of interest (Hayduk & Littvay, 2012). Finally, the Bollen-Stine Bootstrap procedure with 10,000 posterior draws was used to account for the small sample size and multivariate non-normality (Enders, 2010; Muthén & Muthén, 1998 - 2012). This approach uses resampling with replacement to generate a pseudo-population that does not

have attenuated standard errors often associated with small samples (Enders, 2010). Bootstrapped standard errors with 95% confidence intervals (*CI*) thus provide an indication of the precision of the model parameter estimates that are unbiased by small sample size (Enders, 2010). Bias corrected bootstrapped confidence intervals (*BC-CI*) were used for evaluating the statistical significance of indirect (i.e. mediated) effects (Lau & Cheung, 2010). Bootstrapped standard errors are reported in the model figures to facilitate evaluation of the precision of parameter estimates.

3. RESULTS

3.1 CFA Models

Descriptive statistics and intercorrelations for the behavioral ratings and cognitive tasks are provided in supporting information, tables S1 to S4. Results obtained from the CBCL/6-18 revealed that 17 female and 13 male ($n = 30$; 22.4%) participants scored in the *borderline clinical* (T Score 60 – 63, $n = 11$, 8.2%) or *clinical* range (T Score ≥ 64 , $n = 19$, 14.2%) on the DSM-orientated ADHD problems scale, reflecting a sample with ADHD problems across a broad spectrum of severity (Achenbach, 2009). Results for the competing CFA models for the BRIEF, EATQ-R self- and parent-report forms, and the cognitive tasks are displayed in Tables 1 – 4. For the BRIEF, two- and three-factor models provided close fit. However, fit for the two-factor model was superior to the three-factor model as revealed by the Bayes Factor [$BF_{10} = 1.414$] and conditional posterior probability [$(Pr_{BIC}(H_1|D) = .586)$]. Further analyses revealed that the emotional regulation and behavioral regulation factors in the three-factor model did not have discriminant validity, as they shared more variance than they explained in their respective indicators, as calculated by the squared multiple correlation ($SMC = .826$) and average variance extracted ($AVE = .688$ & $.780$) (Fornell & Larcker, 1981; Hair et al., 2010). From the perspective of parsimony, these results suggested that combining these two factors into a single ‘emotion and behavioral regulation’ construct as represented in the two-factor model, was warranted. The two-factor model is displayed in *Figure 1*. These results indicated that summed scores from items composing the metacognition factor and emotional and behavioural regulation factor could be used to capture individual differences in EF as measured by the BRIEF.

The bi-factor model of the EATQ-R originally reported by Snyder et al. (2015) was replicated for both the parent- and self-report forms in the current sample (see Table 2). For the EATQ-R parent-report form, the bifactor model consisted of a Common EC factor and an

activation control-specific group factor with loadings from five of the seven activation control subscale items (see *Figure 2*). Model diagnostics were calculated to assess unidimensionality, including the explained common variance (ECV; i.e. the proportion of item variance explained by the general factor), percentage of uncontaminated correlations (PUC; the number of covariances between items contributing to variance in the general but not the group factor), and omega hierarchical (ω_H ; i.e. a measure of internal consistency reliability of the latent variable) (Rodriguez et al., 2016). These indicated that the majority of variance in EC scale items were captured by the Common EC factor (ECV = .878) with high reliability ($\omega_H = .90$), and low contamination by the group factor (PUC = 93.5%), and could therefore be collapsed into a unidimensional measure without introducing bias in the model (Reise, 2012; Reise et al., 2013; Rodriguez et al., 2016). Calculation of omega hierarchical subscale ($\omega_{Hs} = .248$) for the group factor revealed that there was insufficient reliable residual variance in the activation control-specific group factor to warrant its use as an independent measure (Reise, 2012). Model diagnostics for the EATQ-R self-report form revealed that items forming the activation control-specific group factor did not have sufficient reliable variance ($\omega_{Hs} = .367$) once variance attributable to the Common EC factor was removed. Additionally, a one-factor model provided an adequate fit and was therefore preferred as the more parsimonious model (see *Table 2 & Figure 3*). These results indicated that EC was predominantly a unidimensional construct in the current sample and that raw EC scale scores calculated from the EATQ-R parent- and self-report forms could be used as unbiased estimates of individual differences in EC (Reise, 2012).

Results for the competing measurement models of executive attention are displayed in *Table 4*. A one-factor model provided the most parsimonious fit to the performance-based task data (*Figure 4*). The Bayes Factor demonstrated that the one-factor model was almost three times more likely than the closest fitting competing two-factor model ($BF_{10} = 2.757$). Reliability of this unidimensional executive attention factor was evaluated by calculation of the *H* index, which varies from 0 – 1 with higher values indicating greater construct replicability (Hancock & Mueller, 2001). The *H* index was .82, indicating that the executive attention factor had good construct reliability and was likely to be replicable across studies using the same indicators (Hancock & Mueller, 2001; Rodriguez et al., 2016). Factor score determinacy was also high ($\rho = .901$), suggesting that the factor score estimates calculated for the subsequent structural regression models (see sections 3.3 & 3.4) provided accurate

measures of individual differences with respect to the executive attention latent variable (DiStefano et al., 2009; Grice, 2001).

3.2 Do Behavioral Ratings of Executive Function and Effortful Control Measure the Same Self-Regulation Construct?

A CFA model was estimated to test the first hypothesis that informant ratings of EF and EC would measure the same self-regulation construct. The EF and EC latent variables were each specified from the raw scores calculated for items composing the metacognition factor and emotional and behavioral regulation factor, and the EATQ-R parent- and self-report EC scale raw scores, respectively. The unstandardized factor loadings were constrained to be equal (i.e. tau equivalence) for purposes of statistical identification (Bollen, 1989; Hair et al., 2010). The overall model exhibited adequate fit ($\chi^2(1) = .690, p = .448$; RMSEA = .000 [90%CI = .000, .213]; CFI = 1.000; SRMR = .010) and is displayed in *Figure 5*. The EF and EC factors were correlated near unity and the standardized 95%CI contained one ($\phi = -.970$ [95%CI = -.912, -1.028], $p < .001$), indicating that behavioral ratings of EF and EC converged on a unitary construct. The intercorrelation between EF and EC could not be constrained to one, as it resulted in model misspecification. A unitary 'self-regulation' factor was therefore estimated with loadings from all four variables, with self-reported EC used as the reference variable for factor scaling so that higher values on this latent variable reflected better self-regulation ($\chi^2(2) = 1.774, p = .422$, RMSEA = .000 [90%CI = .000, .165], CFI = 1.000; SRMR = .015). The self-regulation factor is displayed in *Figure 6* and explained almost all the variance in metacognition and parent-reported EC scale scores and just over half of the variance in emotional and behavioral regulation and self-reported EC scale scores. Together, these results indicated that behavioral ratings of EF and EC could be modeled as a unidimensional self-regulation factor for subsequent analyses.

3.3 Does Executive Attention Explain Common Variance in Behavioral Ratings of EF and EC?

Intercorrelations between the executive attention factor score estimates, BRIEF, EATQ-R EC scale scores, and CBCL ADHD problem scale scores are displayed in Table 4. Executive attention was specified as a single indicator latent variable with error variance fixed to reflect the validity coefficient of the factor scores estimates and entered into the measurement model with the self-regulation factor. Overall model fit was adequate ($\chi^2(5) = 3.980, p = .617$, RMSEA = .000 [90%CI = .000, .106]; CFI = 1.000, SRMR = .016) and the

regression of self-regulation onto executive attention was moderately strong and statistically significant ($\gamma = .548$ [95%CI = .416, .681], $p < .001$, see *Figure 7*). These findings indicated that performance measures of executive attention explained just over 30% of the common variance in behavioral ratings of EF and EC.

3.4 Do Performance-Based Tasks and Behavioral Rating Measures of Self-Regulation Explain Unique Variance in ADHD Problems?

The severity of parent-reported ADHD problems was included in the model with the executive attention and self-regulation factor to address the third hypothesis. The DSM-orientated ADHD problems scale of the CBCL was specified as a single indicator latent variable with error variance fixed to reflect the internal consistency reliability of the scale. The covariance between the error variances for the emotional and behavioral regulation factor and ADHD problems was freely estimated ($\theta\epsilon = .236$, $p < .001$) to obtain an adequate fitting model ($\chi^2(7) = 10.517$, $p = .170$, RMSEA = .061 [90%CI = .000, .131], CFI = .993, SRMR = .016). Inspection of the standardized covariance residuals revealed only one exceeding the critical threshold for statistical significance, indicating that the covariance between executive attention factor score estimates and parent reported EC scale scores had been slightly overestimated ($Z = -2.465$, $p = .014$).

A mediation model was conducted to test the third hypothesis that executive attention would explain unique additional variance in ADHD problems to behavioral ratings of EF and EC (i.e. self-regulation). After the self-regulation factor was regressed onto the executive attention factor, the correlation between the self-regulation and ADHD problems factors decreased from .860 to .753, indicating task-based measures of executive attention explained some of the shared variance between behavioral ratings of EF/EC and parent-reported ADHD problems. However, once ADHD problems were regressed onto the self-regulation factor, the initial correlation ($\phi = -.418$, $p < .001$) between the executive attention factor and ADHD problems decreased and was no longer statistically significant ($\psi = .133$, $p = .383$). This parameter was weak and not statistically significant when respecified as a regression coefficient ($\gamma = .068$, $p = .335$). The non-significant correlation between executive attention and ADHD problems was therefore constrained to zero, which did not result in a significantly worse fitting model ($\Delta\chi^2(1) = .931$, $p = .335$). This final model is displayed in *Figure 8* ($\chi^2(8) = 11.448$, $p = .197$, RMSEA = .056 [90%CI = .000, .124], CFI = .994; SRMR = .018). The indirect effect of executive attention on ADHD problems via the self-regulation factor was

moderately strong and statistically significant ($\beta = -.462, p < .001, b = -1.498$ [95%BC-CI = -1.041, -2.028], $p < .001$), explaining 21.3% of the variance. Performance on cognitive tasks thus failed to explain statistically significant additional variance in ADHD problems to that explained by behavioral ratings of EF and EC.

3.5 Evaluating the Direct Effect of Executive Attention on ADHD Problems

It is important to evaluate theoretically plausible alternative and equivalent fitting models, because these represent a challenge to any inferences based on the statistical dependence ('causal') relationships specified in a structural regression model (MacCallum & Austin, 2000a; McDonald & Ho, 2002; Tomarken & Waller, 2005). A theoretically plausible alternative model to the one hypothesized was that self-regulatory ability and ADHD problems are different measures of the same underlying dimension in typically-developing children (i.e. regulation vs dysregulation), and/or are strongly related due to content overlap and common method variance (Bridgett et al., 2013; Espy et al., 2011; Toplak et al., 2013), in addition to a shared association with executive attention. Thus, individual differences in executive attention would be predicted to directly explain variance in both self-regulatory ability and ADHD problems. This alternative model specification was estimated and is displayed in *Figure 9*. Executive attention directly and significantly explained 17.5% of the variance in ADHD problems and 29.4% of the variance in self-regulation. There was a strong and statistically significant residual correlation between self-regulation and ADHD problems ($\psi = -.830, p < .001$), indicating that these constructs shared approximately 69% variance independently of that explained by executive attention.

4. DISCUSSION

This study addressed three questions concerning the relationship between behavioral ratings of EF and EC, performance-based task measures of executive attention and ADHD problems in a typically developing sample. In support of the first hypothesis, we found that EF and EC, as measured by behavioral ratings, were correlated near unity and could be collapsed into a common self-regulation construct. The strong empirical association between the EF and EC factors was not attributable to informant bias, as we used both the self- and parent-report EATQ-R to measure EC. These results assist in clarifying the nature of the proposed conceptual and empirical overlap between EF and EC in children, revealing they are likely the same construct when measured using behavioral ratings (Bridgett et al., 2013; Eisenberg, 2017; Nigg, 2017; Zhou et al., 2012). Until recently, temperament researchers and

cognitive psychologists have investigated self-regulation under distinct rubrics and with a focus on different outcome criteria (Zhou et al., 2012). The current findings may assist in guiding future developmental research towards a more integrated understanding and model of top-down self-regulation during development (Nigg, 2017).

The second hypothesis was partially supported by findings that the executive attention latent variable explained 30% of the common variance in self-regulation as measured by behavioral ratings of EF and EC. The results are consistent with Zhou et al. (2012), who argued that executive attention is a common cognitive mechanism underlying EF and EC. However, the strength of the relationship was far weaker than expected and indicated that the EF and EC constructs, as measured by behavioral ratings, shared substantial common variance beyond that attributable to executive attention. One possible account of these findings can be made with reference to the distinction between ‘cool’ and ‘hot’ EF/self-regulation (Allan & Lonigan, 2011; Bridgett, Burt, Edwards, & Deater-Deckard, 2015; Lin et al., 2019; Zelazo & Cunningham, 2007). Cool EF or behavioral self-regulation refers to goal-directed cognitive processes that occur in emotionally-neutral contexts, whereas hot EF or emotional self-regulation relates to emotionally-laden contexts (Zelazo & Cunningham, 2007). In the current study, executive attention was measured using nine tasks that all assessed emotionally-neutral aspects of cognition and may thus only be related to cool EF and behavioral self-regulation. The unexplained common variance in EF and EC may be those aspects related to emotion self-regulation. However, Lin et al. (2019) recently found that task-based measures of hot and cool self-regulation could not be empirically differentiated within an SEM framework. Thus, an alternative explanation for the current findings is that unexplained variance in the self-regulation factor reflects method variance related to behavioral ratings (Podsakoff et al., 2012). Lack of convergence between the executive attention and self-regulation factors may also be representative of broader issues in mapping task-based measures to behavioral ratings of clinically relevant traits (Cyders & Coskunpinar, 2011; Enkavi et al., 2019).

Our final hypothesis, that performance on cognitive tasks measuring executive attention would explain unique variance in parent-reported ADHD problems in addition to behavioural ratings of self-regulation, was not supported. The results demonstrated that the effect of individual differences in executive attention on parent-reported ADHD problems was fully mediated by behavioral ratings of self-regulation, indicating that these measurement

approaches explain overlapping variance in ADHD problems. This result is in keeping with previous findings in adult samples that behavioral ratings of EF capture most, if not all, the variance explained by performance-based measures, as well as substantial additional unique variance in ADHD symptoms (Barkley & Fischer, 2011; Barkley & Murphy, 2010; Toplak et al., 2008). Our findings contradict previous suggestions that performance on cognitive tasks and behavioral ratings of EF are related to different constructs and explain largely non-overlapping variance in ADHD symptoms (Ten Eycke & Dewey, 2016; Toplak et al., 2013). We suggest that our contrasting findings are due to the use of SEM, which allowed for removal of extraneous sources of variance that would have otherwise attenuated, or even completely obscured, the empirical associations between task-based measures and the behavioral ratings of EF, EC, and ADHD. The comparatively weaker effect of executive attention on ADHD problems compared to the behavioral ratings of self-regulation should be interpreted with respect to common method variance of the questionnaires and the strong content overlap of rating scales assessing EF and ADHD problems, particularly the BRIEF and CBCL (Espy et al., 2011; Podsakoff et al., 2012; Toplak et al., 2013). Indeed, when we modeled the direct effect of executive attention in a theoretically plausible equivalent structural regression model, individual differences in performance on the nine cognitive tasks explained a sizeable proportion (17.5%) of variance in parent-reported severity of ADHD problems.

4.1 Theoretical and Practical Implications

We have provided direct empirical support for the proposed correspondence between EF, specifically working memory and response inhibition, and EC through common mechanisms of executive attention (Nigg, 2017; Zhou et al., 2012). These findings may assist in clarifying some of the ongoing confusion regarding the conceptual and empirical overlap between these two domains (Eisenberg, 2017; Nigg, 2017; Zhou et al., 2012). Our results also support previous proposals that executive attention is the common cognitive mechanism underlying a broad range of higher-order cognitive processes and encourages a more parsimonious approach to developmental self-regulation research (Ilkowska & Engle, 2010; Kane & Engle, 2002; Kaplan & Berman, 2010; McCabe et al., 2010).

The present study also suggests a close association between executive attention and EF. In a review, Diamond (2013) proposed that executive attention and EF exhibited only minimal overlap. However, this proposal was based on conceptualization of executive

attention with respect to the attention networks model and as measured using flanker tasks, not the executive attention theory of WMC. In fact, Diamond (2013) states that executive attention should be thought of as completely synonymous with “*inhibitory control of attention*” or “*selective or focused attention*”, which is subsumed in her model under the broader rubric of interference control and inhibitory control. However, empirical studies in children and adults have shown that inhibitory control of attention (also inference control, selective attention, or attentional inhibition) is only weakly associated with WMC (Kane et al., 2016; Tiego et al., 2018). This suggests that ‘executive attention’ is a much broader construct than is measured by flanker tasks.

Rueda et al. (2011) previously acknowledged strong correspondence between the working memory Central Executive and executive attention as conceptualized within the attention networks model. However, these authors have focused on conflict monitoring and adaptation processes, thereby neglecting the broader range of control functions attributable to executive attention (Rueda et al., 2011). A narrow conceptualization of executive attention in relation to developmental self-regulation may lead to erroneous conclusions regarding development and interrelationships with other important aspects of functioning. For example, developmental improvements in performance on the attention network test plateau around 7 years of age (Rueda, Fan, et al., 2004), whereas task performance on tests of WMC and response inhibition continue to improve into adolescence and early adulthood (Best & Miller, 2010; Lee, Bull, & Ho, 2013; Luna, Marek, Larsen, Tervo-Clemmens, & Chahal, 2015). This suggests that stimulus-response compatibility tasks measure relatively low-level aspects of executive attention, which mature earlier and may not be as integral to self-regulation as high-level aspects of executive attention. Our findings suggest that stimulus-response compatibility tasks, such as the attention networks test, Stroop, flanker, and Simon tasks, may not provide adequate measures of executive attention, EC, and self-regulation more broadly. This conclusion is supported by recent evidence documenting the poor reliability of cognitive tasks, particularly those using difference scores between conditions, as measures of individual differences in self-regulation (Enkavi et al., 2019; Hedge et al., 2017).

EFs, such as WMC and response inhibition, represent the cognitive underpinnings for instantiating self-regulatory strategies, such as delay of gratification and emotion regulation (Banfield, Wyland, Macrae, Munte, & Heatherton, 2004; Ellis, Rothbart, & Posner, 2004; McRae, Jacobs, Ray, John, & Gross, 2012; Ochsner & Gross, 2005; Pe, Raes, & Kuppens,

2013). Individual differences in cognitive capacity, as measured in optimal performance contexts using performance-based tasks, represent a potential constraint (i.e. upper bound) on the efficiency and success with which self-regulatory processes can be implemented in ecologically valid contexts. Indeed, empirical research in adult and developmental samples indicates that individual differences in WMC and response inhibition as assessed with performance-based tasks have direct bearing on the success with which self-regulation is achieved at a behavioral level (Barrett, Tugade, & Engle, 2004; Hofmann et al., 2008; Schmeichel et al., 2008; Yu et al., 2016). Our results are consistent with these previous findings in that individual differences in executive attention, measured across nine cognitive tasks, explained almost a third of the variance in self- and parent-reported self-regulatory ability.

Conversely, executive attention deficits may lead to self-regulatory failures associated with limitations in cognitive capacity, with subsequent implications for symptoms of developmental psychopathology (Barkley, 2014; Kotabe & Hofmann, 2015; Nigg, 2017b). Our finding that the direct effect of executive attention explained 17.5% of the variance in parent-reported ADHD problems is consistent with models of self-regulatory failure and previous research linking EF deficits to ADHD (Willcutt, Doyle, Nigg, Faraone, & Pennington, 2005). Nevertheless, our finding that executive attention failed to explain unique variance in parent-reported ADHD problems beyond that explained by behavioral ratings raises questions about the utility of cognitive assessment in self-regulation and developmental psychopathology research. Performance on cognitive tasks related to self-regulation are generally associated with low internal consistency reliability, poor stability, and may be ill-suited for measuring individual differences, particularly those purported to reflect stable traits (Enkavi et al., 2019; Hedge et al., 2017). Despite being more costly and time-intensive, cognitive assessment may offer limited incremental predictive validity in explaining developmental psychopathology beyond behavioral ratings of self-regulation (Barkley & Fischer, 2011; Barkley & Murphy, 2010; Toplak et al., 2008).

4.2 Limitations

“Executive Attention”, “Executive Function”, and “Effortful Control” are each superordinate constructs that encompass multiple component processes and for which a number of theoretical accounts and models exist (Nigg, 2017). This ambiguity, along with a proliferation of terminology in the literature, makes it difficult to delineate the theoretical and

empirical boundaries between these constructs. Our account is just one potential framework for theoretical and empirical integration. Additionally, we did not directly test the empirical overlap between stimulus-response compatibility tasks with measures of WMC, response inhibition, and general intelligence. Nor did we examine the neural mechanisms underlying performance of these tasks and, purportedly, self-regulation and EC according to the attention networks model (Posner & Rothbart, 2009). Our study was also limited to examining the interrelationships between cognitive tasks measuring WMC, response inhibition, and psychometric *g*. It is possible that use of a wider variety of tasks would result in greater differentiation of the executive attention construct and identify divergent relationships of these component cognitive processes with behavioral ratings of EF, EC, and ADHD problems. Thus, we are unable to draw definitive conclusions with regard to the overlap or differentiation of these constructs at a cognitive or neural level. Future studies could attempt to distinguish between executive attention mechanisms of maintenance and disengagement, include EF measures of updating and switching, differentiate between hot and cool self-regulation, as well as examine the common and distinct neural mechanisms underlying executive attention, EF, and EC (Engle, 2018; Hofmann, Schmeichel, & Baddeley, 2012; Lin et al., 2019).

Our sample size of 136 is small for analysis using SEM according to general guidelines (Kline, 2015). It is more difficult to detect evidence of model misspecification, as well as compare fit between competing models with small samples. We used a combination of statistical techniques to circumvent this problem, including a jigsaw piece modeling strategy, factor scores regression, single-indicator latent variables, bootstrapping, and reference to coefficients and standardized covariance residuals as measures of local model fit. This approach enabled us to conserve the number of free parameters estimated, maintain a higher participant number to parameter ratio, whilst also guarding against attenuated standard errors and confidence intervals for the parameter estimates. SEM can be a powerful statistical technique for testing hypotheses even in small samples, which are considered sufficient when analyses converge on solutions without illogical parameter estimates or attenuated standard errors (Gignac, 2006). Nevertheless, replication in a larger sample will be required to validate the precision of the parameter estimates and the conclusions of the study (Hermida, Luchman, Nicolaidis, & Wilcox, 2015).

It is not possible to determine the correct specification for a mediational model using cross-sectional data based on model fit statistics or the strength and significance of parameter estimates (Wiedermann & von Eye, 2015). We have presented an alternative model positing direct effects of executive attention on self-regulation and ADHD problems; however, other less theoretically plausible models are also possible (McDonald & Ho, 2002; Tomarken & Waller, 2005). Conclusions based on cross-sectional data are also limited by concerns of low test-retest reliability for cognitive tasks (Enkavi et al., 2019). A carefully designed longitudinal study would be required to demonstrate that the hypothesized mediational model provides the most accurate representation compared to competing models (MacCallum & Austin, 2000).

We chose to focus on a narrow age range in the current study to reduce the impact of developmental changes in executive attention on the results (Wiebe et al., 2008). However, this limits generalizability due to the protracted development of the neural networks underlying working memory and response inhibition, as well as their divergent developmental trajectories (Best & Miller, 2010; Luna et al., 2015). Thus, further study of these relationships across a broader developmental period is needed. Additionally, empirical relationships between the constructs of interest may have been attenuated in the current study because of fewer cognitive problems and a lower endorsement of ADHD problems in typically-developing children compared to a clinical sample (Espy et al., 2011). This may partly explain discrepancies in our results compared to previous studies, which have used either clinical, or mixed clinical and non-clinical, developmental samples (Toplak et al., 2008; Toplak et al., 2013). For example, a uniform lack of difficulties in EF as revealed by consistently low behavioral ratings across the BRIEF scales could result in more difficulty distinguishing between the emotional regulation and behavioral regulation subfactors (Egeland & Fallmyr, 2010). Replication across a diverse range of clinical samples, particularly children diagnosed with ADHD, would be required to validate the current findings.

ADHD is a heterogeneous disorder comprising multiple subtypes associated with distinct etiological mechanisms and it is probable that only a subset of cases are related to specific EF deficits (APA, 2013; Diamond, 2005; Fair, Bathula, Nikolas, & Nigg, 2012; Frick & Nigg, 2012; Nigg, Willcutt, Doyle, & Sonuga-Barke, 2005; Sonuga-Barke, 2003). Measurement of ADHD problems as a unitary construct constitutes an important limitation of

this study and may have obscured empirical relationships between specific constellations of symptoms with executive attention and EF/EC. Distinguishing between clinical presentations (i.e. Inattention, Impulsivity/Hyperactivity, & Combined) using categorical specifiers and/or continuous symptom counts, or alternatively empirically-derived latent classes, could be important avenues for investigating the relationships between ADHD problems and self-regulation constructs in future studies (Fair et al., 2012; Lahey & Willcutt, 2010). Measuring ADHD problems using only one informant also limits the implications of the study, because symptom severity and presentation can vary across contexts (Hinshaw, 2018). Multiple informants would be needed to capture consistencies and differences in problem behaviours across contexts, such as the classroom and home environment (Achenbach & Rescorla, 2001).

4.3 Conclusions

We have shown that behavioral ratings of EF and EC measured the same self-regulation construct, thereby clarifying some of the ongoing confusion regarding the conceptual and empirical overlap between these two domains. We also found that a unitary model of executive attention derived from performance on cognitive tasks measuring WMC, response inhibition, and general intelligence, failed to explain statistically significant unique variance in parent-reported ADHD problems beyond behavioral ratings of EF and EC. Individual differences in cognitive capacity may represent a constraint on the instantiation of effective self-regulation in typical, everyday contexts. Nevertheless, these findings raise questions about the utility of cognitive assessment for understanding individual differences in self-regulation and developmental psychopathology.

Data Availability Statement

The dataset analyzed for this study can be found on PsyArXiv Open Science Framework [<https://osf.io/hq4xy/>].

REFERENCES

- Achenbach, T. M. (2009). *The Achenbach System of Empirically Based Assessment (ASEBA): Development, findings, theory, and applications*. Burlington, VT: University of Vermont, Research Center for Children, Youth, & Families.
- Achenbach, T. M., & Rescorla, L. A. (2001). *Manual for the ASEBA school-age forms & profiles*. Burlington, VT: University of Vermont, Research Center for Children, Youth, & Families.
- Allan, N. P., & Lonigan, C. J. (2011). Examining the dimensionality of effortful control in preschool children and its relation to academic and socioemotional indicators. *Developmental Psychology, 47*, 905 - 915.
- Alloway, T. P. (2007). *Automated working memory assessment*. London: Pearson Assessment.
- Alloway, T. P., Gathercole, S. E., & Pickering, S. J. (2006). Verbal and visuospatial short-term and working memory in children: Are they separable? *Child Development, 77*, 1698-1716.
- Anderson, V. A., Anderson, P., Northam, E., Jacobs, R., & Mikiewicz, O. (2002). Relationships between cognitive and behavioral measures of executive function in children with brain disease. *Child Neuropsychology, 8*(4), 231-240. Retrieved from <Go to ISI>://WOS:000182989700002
- APA. (2000). *Diagnostic and statistical manual of mental disorders: DSM-IV-TR*. (4th Text Revised ed.). Washington DC: American Psychiatric Association.
- APA. (2013). *Diagnostic and statistical manual of mental disorders (DSM-5®)*: American Psychiatric Pub.
- Aron, A. R., & Verbruggen, F. (2008). Stop the presses: Dissociating a selective from a global mechanism for stopping. *Psychological Science, 19*, 1146-1153. doi:10.1111/j.1467-9280.2008.02216.x
- Awh, E., Jonides, J., & Reuter-Lorenz, P. A. (1998). Rehearsal in spatial working memory. *Journal of Experimental Psychology: Human Perception and Performance, 24*(), 780 - 790.

- Baddeley, A., & Hitch, G. (1974). Working memory. *The psychology of learning and motivation*, 8, 47 - 89.
- Baddeley, A. (2003). Working memory: Looking back and looking forward. *Nature reviews. Neuroscience*, 4, 829 - 839.
- Baddeley, A. (2012). Working memory: Theories, models, and controversies. *Annual Review of Psychology*, 63, 1 - 29. doi:10.1146/annurev-psych-120710-100422
- Bandalos, D. L. (2002). The Effects of Item Parceling on Goodness-of-Fit and Parameter Estimate Bias in Structural Equation Modeling. *Structural equation modeling: a multidisciplinary journal*, 9(1), 78 - 102. doi:10.1207/S15328007SEM0901_5
- Banfield, J. F., Wyland, C. L., Macrae, C. N., Munte, T. F., & Heatherton, T. F. (2004). The cognitive neuroscience of self-regulation. In R. F. Baumeister & K. D. Vohs (Eds.), *Handbook of self-regulation: Research, theory, and applications*. (pp. 62 - 83). New York: The Guilford Press.
- Banich, M. T. (2009). Executive function: The search for an integrated account. *Current Directions In Psychological Science*, 18, 89 - 94.
- Barbey, A. K., Colom, R., Solomon, J., Krueger, F., Forbes, C., & Grafman, J. (2012). An integrative architecture for general intelligence and executive function revealed by lesion mapping. *Brain*, 135, 1154 - 1164. doi:10.1093/brain/aws021
- Barkley, R. A. (2014). Attention-deficit/hyperactivity disorder, self-regulation, and executive functioning. In K. D. Vohs & R. F. Baumeister (Eds.), *Handbook of self-regulation: Research, theory, and applications* (pp. 551 - 592). New York: Guilford Publications.
- Barkley, R. A., & Fischer, M. (2011). Predicting Impairment in Major Life Activities and Occupational Functioning in Hyperactive Children as Adults: Self-Reported Executive Function (EF) Deficits Versus EF Tests. *Developmental Neuropsychology*, 36(2), 137-161. doi:10.1080/87565641.2010.549877
- Barkley, R. A., & Murphy, K. R. (2010). Impairment in Occupational Functioning and Adult ADHD: The Predictive Utility of Executive Function (EF) Ratings Versus EF Tests. *Archives of Clinical Neuropsychology*, 25(3), 157-173. doi:10.1093/arclin/acq014

- Barrett, L. F., Tugade, M. M., & Engle, R. W. (2004). Individual differences in working memory capacity and dual-process theories of the mind. *Psychological Bulletin*, *130*, 553 - 573. doi:10.1037/0033-2909.130.4.553
- Barrett, P. Q. (2007). Structural equation modelling: Adjudging model fit. *Personality and Individual Differences*, *42*(5), 815-824. doi: <https://doi.org/10.1016/j.paid.2006.09.018>
- Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, *57*(1), 289-300.
- Best, J. R., & Miller, P. H. (2010). A developmental perspective on executive function. *Child Development*, *81*, 1641-1660. doi:10.1111/j.1467-8624.2010.01499.x
- Bollen, K. A. (1989). *Structural equations with latent variables*. New York Wiley.
- Bollen, K. A. (2000). Modeling strategies: In search of the holy grail. *Structural equation modeling*, *7*, 74 - 81.
- Bridgett, D. J., Burt, N. M., Edwards, E. S., & Deater-Deckard, K. (2015). Intergenerational Transmission of Self-Regulation: A Multidisciplinary Review and Integrative Conceptual Framework. *Psychological Bulletin*, *141*(3), 602-654. doi:10.1037/a0038662
- Bridgett, D. J., Oddi, K. B., Laake, L. M., Murdock, K. W., & Bachmann, M. N. (2013). Integrating and differentiating aspects of self-regulation: Effortful control, executive functioning, and links to negative affectivity. *Emotion*, *13*, 47 - 63. doi:10.1037/a0029536
- Brydges, C. R., Reid, C. L., Fox, A. M., & Anderson, M. (2012). A unitary executive function predicts intelligence in children. *Intelligence*, *40*, 458-469. doi:10.1016/j.intell.2012.05.006
- Burgoyne, A. P., Hambrick, D. Z., & Altmann, E. M. (2019). Is working memory capacity a causal factor in fluid intelligence? *Psychon Bull Rev*, *26*(4), 1333-1339. doi:10.3758/s13423-019-01606-9
- Burnham, B. R., Sabia, M., & Langan, C. (2014). Components of working memory and visual selective attention. *Journal of Experimental Psychology - Human Perception and Performance*, *40*, 391 - 403. doi:10.1037/a0033753

- Byrne, B. M. (2012). *Structural equation modeling with Mplus: Basic concepts, applications, and programming*. New York: Routledge.
- Case, R. D., Kurland, M., & Goldberg, J. (1982). Operational efficiency and the growth of short-term memory span. *Journal of Experimental Child Psychology*, *33*, 386 - 404.
- Chambers, C. D., Garavan, H., & Bellgrove, M. A. (2009). Insights into the neural basis of response inhibition from cognitive and clinical neuroscience. *Neuroscience and Biobehavioral Reviews*, *33*, 631-646. doi:10.1016/j.neubiorev.2008.08.016
- Coghill, D., & Sonuga-Barke, E. J. S. (2012). Annual Research Review: Categories versus dimensions in the classification and conceptualisation of child and adolescent mental disorders – implications of recent empirical study. *Journal of Child Psychology and Psychiatry*, *53*(5), 469-489. doi:10.1111/j.1469-7610.2011.02511.x
- Cohen, J., & Cohen, P. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.
- Conway, A. R. A., Kane, M. J., & Engle, R. W. (2003). Working memory capacity and its relation to general intelligence. *Trends in Cognitive Sciences*, *7*, 547 - 552.
- Conway, A. R. A., Kane, M. J., Bunting, M. F., Hambrick, D. Z., Wilhelm, O., & Engle, R. W. (2005). Working memory span tasks: A methodological review and user's guide. *Psychonomic Bulletin & Review*, *12*, 769 - 786.
- Conway, A. R. A., Kane, M. J., & Engle, R. W. (2003). Working memory capacity and its relation to general intelligence. *Trends in Cognitive Sciences*, *7*, 547 - 552.
- Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience*, *3*, 201-215. doi:10.1038/nrn755
- Cribbie, R. A. (2007). Multiplicity control in structural equation modeling. *Structural equation modeling*, *14*, 98-112. doi:10.1207/s15328007sem1401_5
- Cuthbert, B. N. (2014). The RDoC framework: facilitating transition from ICD/DSM to dimensional approaches that integrate neuroscience and psychopathology. *World Psychiatry*, *13*(1), 28-35. doi:10.1002/wps.20087
- Cyders, M. A., & Coskunpinar, A. (2011). Measurement of constructs using self-report and behavioral lab tasks: is there overlap in nomothetic span and construct representation for impulsivity? *Clin Psychol Rev*, *31*(6), 965-982. doi:10.1016/j.cpr.2011.06.001

- Daneman, M., & Carpenter, P. A. (1980). Individual differences in working memory and reading. *Journal of verbal learning and verbal behavior*, *19*, 450 - 466.
- DeCarlo, L. T. (1997). On the meaning and use of kurtosis. *Psychological methods*, *2*(3), 292 - 307.
- Derryberry, D., & Rothbart, M. K. (1988). Arousal, affect, and attention as components of temperament. *Journal of Personality and Social Psychology*, *55*, 958 - 966.
doi:10.1037/0022-3514.55.6.958
- Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, *18*, 193-222. doi:10.1146/annurev.neuro.18.1.193
- Devlieger, I., Mayer, A., & Rosseel, Y. (2016). Hypothesis testing using factor score regression: A comparison of four methods. *Educational and Psychological Measurement*, *76*(5), 741 - 770. doi:10.1177/0013164415607618
- Devlieger, I., & Rosseel, Y. (2017). Factor score path analysis. *Methodology*, *13*(Supplement 1), 31-38. doi:10.1027/1614-2241/a000130
- Diamond, A. (2005). Attention-deficit disorder (attention-deficit/ hyperactivity disorder without hyperactivity): a neurobiologically and behaviorally distinct disorder from attention-deficit/hyperactivity disorder (with hyperactivity). *Dev Psychopathol*, *17*(3), 807-825. doi:10.1017/S0954579405050388
- Diamond, A. (2013). Executive functions. *Annual Review of Psychology*, *64*, 135-168.
doi:10.1146/annurev-psych-113011-143750
- DiStefano, C., Zhu, M., & Mindrila, D. (2009). Understanding and using factor scores: Considerations for the applied researcher. *Practical Assessment, Research & Evaluation*, *14*(20), 1 - 11.
- Downing, P. E. (2000). Interactions between visual working memory and selective attention. *Psychological Science*, *11*, 467 - 473.
- Egeland, J., & Fallmyr, O. (2010). Confirmatory Factor Analysis of the Behavior Rating Inventory of Executive Function (BRIEF): Support for a distinction between emotional and behavioral regulation. *Child Neuropsychol*, *16*(4), 326-337.
doi:10.1080/09297041003601462

- Eisenberg, N. (2017). Commentary: What's in a word (or words) - on the relations among self-regulation, self-control, executive functioning, effortful control, cognitive control, impulsivity, risk-taking, and inhibition for developmental psychopathology - reflections on Nigg (2017). *J Child Psychol Psychiatry*, 58(4), 384-386. doi:10.1111/jcpp.12707
- Eisenberg, N., Hofer, C., & Vaughan, J. (2007). Effortful control and its socioemotional consequences. In J. J. Gross (Ed.), *Handbook of emotion regulation*. (pp. 287 - 306). New York: The Guilford Press.
- Eisenberg, N., Smith, C. L., Sadovsky, A., & Spinrad, T. L. (2004). Effortful control: Relations with emotion regulation, adjustment and socialization in childhood. In R. F. Baumeister & K. D. Vohs (Eds.), *Handbook of self-regulation: Research, theory, and applications*. (pp. 259 - 282). New York: The Guilford Press.
- Ellis, L. K., & Rothbart, M. K. (2001). *Revision of the early adolescent temperament questionnaire*. Paper presented at the Biennial Meeting of the Society for Research in Child Development, Minneapolis, Minnesota.
- Ellis, L. K., Rothbart, M. K., & Posner, M. I. (2004). Individual differences in executive attention predict self-regulation and adolescent psychosocial behaviors. *Annals of the New York Academy of Sciences*, 1021, 337-340. doi:10.1196/annals.1308.041
- Enders, C. K. (2010). *Applied missing data analysis*. New York: The Guilford Press.
- Engel de Abreu, P. M. J., Conway, A. R. A., & Gathercole, S. E. (2010). Working memory and fluid intelligence in young children. *Intelligence*, 38, 552 - 561.
- Engle, R. W. (2002). Working memory capacity as executive attention. *Current Directions In Psychological Science*, 11, 19 - 23. doi:10.1111/1467-8721.00160
- Engle, R. W. (2018). Working Memory and Executive Attention: A Revisit. *Perspect Psychol Sci*, 13(2), 190-193. doi:10.1177/1745691617720478
- Enkavi, A. Z., Eisenberg, I. W., Bissett, P. G., Mazza, G. L., MacKinnon, D. P., Marsch, L. A., & Poldrack, R. A. (2019). Large-scale analysis of test-retest reliabilities of self-regulation measures. *Proceedings of the National Academy of Sciences*, 201818430. doi:10.1073/pnas.1818430116
- Eriksen, C. W. (1995). The flankers task and response competition: A useful tool for investigating a variety of cognitive problems. *Visual Cognition*, 2, 101 - 118.

- Espy, K. A., Sheffield, T. D., Wiebe, S. A., Clark, C. A., & Moehr, M. J. (2011). Executive control and dimensions of problem behaviors in preschool children. *Journal of Child Psychology and Psychiatry*, *52*, 33 - 46. doi:10.1111/j.1469-7610.2010.02265.x
- Fair, D. A., Bathula, D., Nikolas, M. A., & Nigg, J. T. (2012). Distinct neuropsychological subgroups in typically developing youth inform heterogeneity in children with ADHD. *Proceedings of the National Academy of Sciences*, *109*(17), 6769-6774. doi:10.1073/pnas.1115365109
- Fan, J., Flombaum, J. I., McCandliss, B. D., Thomas, K. M., & Posner, M. I. (2003). Cognitive and brain consequences of conflict. *Neuroimage*, *18*, 42 - 57. doi:10.1006/nimg.2002.1319
- Fan, J., McCandliss, B. D., Sommer, T., Raz, A., & Posner, M. I. (2002). Testing the efficiency and independence of attentional networks. *Journal of Cognitive Neuroscience*, *14*, 340 - 347. doi:10.1162/089892902317361886
- Fan, J., Raz, A., & Posner, M. I. (2003). Attentional mechanisms. In *Encyclopedia of the Neurological Sciences*: Elsevier Science.
- Fitzpatrick, C., & Schraw, G. (2003). Test review of the Behavior Rating Inventory of Executive Function. The fifteenth mental measurements yearbook [electronic version] In B. S. Plake, J. C. Impara, & R. A. Spies (Eds.).
- Flanagan, D. P., & Kaufman, A. S. (2004). *Essentials of WISC-IV assessment*. Hoboken: John Wiley & Sons, Inc.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 39-50.
- Forstmann, B. U., Jahfari, S., Scholte, H. S., Wolfensteller, U., van den Wildenberg, W. P., & Ridderinkhof, K. R. (2008). Function and structure of the right inferior frontal cortex predict individual differences in response inhibition: A model-based approach. *The Journal of Neuroscience*, *28*, 9790 - 9796. doi:10.1523/JNEUROSCI.1465-08.2008
- Fournet, N., Roulin, J. L., Monnier, C., Atzeni, T., Cosnefroy, O., Le Gall, D., & Roy, A. (2015). Multigroup confirmatory factor analysis and structural invariance with age of the Behavior Rating Inventory of Executive Function (BRIEF)--French version. *Child Neuropsychol*, *21*(3), 379-398. doi:10.1080/09297049.2014.906569

- Frick, P. J., & Nigg, J. T. (2012). Current issues in the diagnosis of attention deficit hyperactivity disorder, oppositional defiant disorder, and conduct disorder. *Annu Rev Clin Psychol*, *8*, 77-107. doi:10.1146/annurev-clinpsy-032511-143150
- Friedman, N. P., Miyake, A., Robinson, J. L., & Hewitt, J. K. (2011). Developmental trajectories in toddlers' self-restraint predict individual differences in executive functions 14 years later: A behavioral genetic analysis. *Developmental Psychology*, *47*, 1410-1430. doi:10.1037/a0023750
- Friedman, N. P., Miyake, A., Young, S. E., DeFries, J. C., Corley, R. P., & Hewitt, J. K. (2008). Individual differences in executive functions are almost entirely genetic in origin. *Journal of Experimental Psychology: General*, *137*, 201-225. doi:10.1037/0096-3445.137.2.201
- Friedman, N. P., & Miyake, A. (2017). Unity and diversity of executive functions: Individual differences as a window on cognitive structure. *Cortex*, *86*, 186-204. doi:10.1016/j.cortex.2016.04.023
- Gathercole, S. E., Pickering, S. J., Ambridge, B., & Wearing, H. (2004). The structure of working memory from 4 to 15 years of age. *Developmental Psychology*, *40*, 177-190. doi:10.1037/0012-1649.40.2.177
- Ghiselli, E. E., Campbell, J. P., & Zedeck, S. (1981). *Measurement theory for the behavioral sciences*: WH Freeman.
- Gignac, G. E. (2006). Self-reported emotional intelligence and life satisfaction: Testing incremental predictive validity hypotheses via structural equation modeling (SEM) in a small sample. *Personality and Individual Differences*, *40*(8), 1569-1577. doi: https://doi.org/10.1016/j.paid.2006.01.001
- Gioia, G. A., Isquith, P. K., Guy, S. C., & Kenworthy, L. (2000). *BRIEF: Behavioral rating inventory of executive function professional manual*. Lutz, FL: Psychological Assessment Resources, Inc.
- Gioia, G. A., Isquith, P. K., Retzlaff, P. D., & Espy, K. A. (2002). Confirmatory factor analysis of the Behavior Rating Inventory of Executive Function (BRIEF) in a clinical sample. *Child Neuropsychology*, *8*, 249 - 257. doi:10.1076/chin.8.4.249.13513
- Grice, J. W. (2001). Computing and evaluating factor scores. *Psychological methods*, *6*(4), 430-450.

- Hair, J. F., Black, C. W., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). New Jersey: Prentice Hall.
- Hancock, G. R., & Mueller, R. O. (2001). Rethinking construct reliability within latent variable systems. In R. Cudeck, S. du Toit, & D. Sorbom (Eds.), *Structural equation modeling: Present and future - A festschrift in honor of Karl Joreskog*. (pp. 195-216). Lincolnwood, IL: Scientific Software International.
- Hayduk, L. A., Cummings, G., Boadu, K., Pazderka-Robinson, H., & Boulianne, S. (2007). Testing! testing! one, two, three – Testing the theory in structural equation models! *Personality and Individual Differences, 42*(5), 841-850. doi: <https://doi.org/10.1016/j.paid.2006.10.001>
- Hayduk, L. A., & Littvay, L. (2012). Should researchers use single indicators, best indicators, or multiple indicators in structural equation models? *BMC Med Res Methodol, 12*, 159. doi:10.1186/1471-2288-12-159
- Hedge, C., Powell, G., & Sumner, P. (2017). The reliability paradox: Why robust cognitive tasks do not produce reliable individual differences. *Behavior Research Methods, 1*–21. doi: <https://doi.org/10.3758/s13428-017-0935-1>
- Heitz, R. P., & Engle, R. W. (2007). Focusing the spotlight: Individual differences in visual attention control. *Journal of Experimental Psychology: General, 136*, 217 - 240. doi:10.1037/0096-3445.136.2.217
- Helzer, J. E., Kraemer, H. C., & Krueger, R. F. (2006). The feasibility and need for dimensional psychiatric diagnoses. *Psychol Med, 36*(12), 1671-1680. doi:10.1017/S003329170600821X
- Hermida, R., Luchman, J. N., Nicolaidis, V., & Wilcox, C. (2015). The issue of statistical power for overall model fit in evaluating structural equation models. *Computational Methods in Social Sciences, 3*, 25 - 42.
- Hinshaw, S. P. (2018). Attention Deficit Hyperactivity Disorder (ADHD): Controversy, Developmental Mechanisms, and Multiple Levels of Analysis. *Annu Rev Clin Psychol, 14*, 291-316. doi:10.1146/annurev-clinpsy-050817-084917
- Hoaglin, D. C., & Iglewicz, B. (1987). Fine-tuning some resistant rules for outlier labeling. *Journal of the American Statistical Association, 82*(400), 1147 - 1149.

- Hofmann, W., Friese, M., Schmeichel, B. J., & Baddeley, A. D. (2011). Working memory and self-regulation. In K. D. Vohs & R. F. Baumeister (Eds.), *Handbook of self-regulation: Research, theory, and applications* (2nd ed., pp. 204 - 225). New York: The Guilford Press.
- Hofmann, W., Gschwendner, T., Friese, M., Wiers, R. W., & Schmitt, M. (2008). Working memory capacity and self-regulatory behavior: Toward an individual differences perspective on behavior determination by automatic versus controlled processes. *Journal of Personality and Social Psychology, 95*, 962 - 977.
- Hofmann, W., Schmeichel, B. J., & Baddeley, A. D. (2012). Executive functions and self-regulation. *Trends Cogn Sci, 16*(3), 174-180. doi:10.1016/j.tics.2012.01.006
- Holzman, J. B., & Bridgett, D. J. (2017). Heart rate variability indices as bio-markers of top-down self-regulatory mechanisms: A meta-analytic review. *Neuroscience and Biobehavioral Reviews, 74*, 233-255. doi:10.1016/j.neubiorev.2016.12.032
- Hudziak, J. J., Achenbach, T. M., Althoff, R. R., & Pine, D. S. (2007). A dimensional approach to developmental psychopathology. *Int J Methods Psychiatr Res, 16 Suppl 1*, S16-23. doi:10.1002/mpr.217
- Ilkowska, M., & Engle, R. W. (2010). Working memory capacity and self-regulation. In R. H. Hoyle (Ed.), *Handbook of personality and self-regulation* (pp. 263 - 290). Oxford, UK: Wiley-Blackwell.
- Jackson, D. L. (2003). Revisiting sample size and number of parameter estimates: Some support for the N : q hypothesis. *Structural equation modeling, 10*, 128 - 141. doi:10.1207/s15328007sem1001_6
- Jarosz, A. F., & Wiley, J. (2014). What are the odds? A practical guide to computing and reporting Bayes factors. *The Journal of Problem Solving, 7*(1). doi:10.7771/1932-6246.1167
- Jensen, A. R. (2002). Psychometric g: Definition and substantiation. In R. J. Sternberg & E. L. Grigorenko (Eds.), *The general factor of intelligence: How general is it?* (pp. 39-53). Mahwah, NJ.: Lawrence Erlbaum Associates.
- Kane, M. J., Bleckley, M. K., Conway, A. R. A., & Engle, R. W. (2001). A controlled-attention view of working-memory capacity. *Journal of Experimental Psychology: General, 130*, 169-183. doi:10.1037/0096-3445.130.2.169

- Kane, M. J., Conway, A. R. A., Hambrick, D. Z., & Engle, R. W. (2007). Variation in working memory capacity as variation in executive attention and control. In A. R. Conway, C. Jarrold, M. J. Kane, A. Miyake, & J. N. Towse (Eds.), *Variation in working memory* (pp. 21 - 48). New York: Oxford University Press.
- Kane, M. J., & Engle, R. W. (2002). The role of prefrontal cortex in working-memory capacity, executive attention, and general fluid intelligence: An individual-differences perspective. *Psychonomic Bulletin & Review*, *9*, 637 - 671. doi:10.3758/BF03196323
- Kane, M. J., & Engle, R. W. (2003). Working-memory capacity and the control of attention: The contributions of goal neglect, response competition, and task set to Stroop interference. *Journal of Experimental Psychology: General*, *132*, 47 - 70.
- Kane, M. J., Meier, M. E., Smeekens, B. A., Gross, G. M., Chun, C. A., Silvia, P. J., & Kwapil, T. R. (2016). Individual differences in the executive control of attention, memory, and thought, and their associations with schizotypy. *Journal of Experimental Psychology: General*, *145*, 1017-1048. doi:10.1037/xge0000184
- Kaplan, S., & Berman, M. G. (2010). Directed attention as a common resource for executive functioning and self-regulation. *Perspectives on Psychological Science*, *5*, 43 - 57. doi:10.1177/1745691609356784
- Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The Performance of RMSEA in Models With Small Degrees of Freedom. *Sociological Methods & Research*, *44*(3), 486-507. doi:10.1177/0049124114543236
- Kline, R. B. (2015). *Principles and practice of structural equation modeling* (4th ed.). New York: The Guilford Press.
- Kochanska, G., Murray, K. T., & Harlan, E. T. (2000). Effortful control in early childhood: Continuity and change, antecedents, and implications for social development. *Developmental Psychology*, *36*, 220 -232.
- Kornblum, S., Hasbroucq, T., & Osman, A. (1990). Dimensional overlap: Cognitive basis for stimulus-response compatibility - A model and taxonomy. *Psychological Review*, *97*, 253-270. doi:10.1037/0033-295X.97.2.253
- Kotabe, H. P., & Hofmann, W. (2015). On integrating the components of self-control. *Perspectives on Psychological Science*, *10*, 618 - 638. doi:10.1177/1745691615593382

- Kraemer, H. C., Noda, A., & O'Hara, R. (2004). Categorical versus dimensional approaches to diagnosis: methodological challenges. *Journal of psychiatric research, 38*(1), 17-25. doi:[https://doi.org/10.1016/S0022-3956\(03\)00097-9](https://doi.org/10.1016/S0022-3956(03)00097-9)
- Krueger, R. F., Kotov, R., Watson, D., Forbes, M. K., Eaton, N. R., Ruggero, C. J., . . . Zimmermann, J. (2018). Progress in achieving quantitative classification of psychopathology. *World Psychiatry, 17*(3), 282-293. doi:10.1002/wps.20566
- Lahey, B. B., & Willcutt, E. G. (2010). Predictive validity of a continuous alternative to nominal subtypes of attention-deficit/hyperactivity disorder for DSM-V. *J Clin Child Adolesc Psychol, 39*(6), 761-775. doi:10.1080/15374416.2010.517173
- Lau, R. S., & Cheung, G. W. (2010). Estimating and comparing specific mediation effects in complex latent variable models. *Organizational Research Methods, 15*, 3 - 16. doi:10.1177/1094428110391673
- Lee, K., Bull, R., & Ho, R. M. (2013). Developmental changes in executive functioning. *Child Development, 84*, 1933-1953. doi:10.1111/cdev.12096
- Lin, B., Liew, J., & Perez, M. (2019). Measurement of self-regulation in early childhood: Relations between laboratory and performance-based measures of effortful control and executive functioning. *Early Child Res Q, 47*, 1-8. doi:10.1016/j.ecresq.2018.10.004
- Lipszyc, J., & Schachar, R. (2010). Inhibitory control and psychopathology: A meta-analysis of studies using the stop signal task. *Journal of the International Neuropsychological Society, 16*, 1064 - 1076. doi:10.1017/S1355617710000895
- Little, R. J. A. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association, 83*, 1198 - 1202.
- Little, C. W., Taylor, J., Moltisanti, A., Ennis, C., Hart, S. A., & Schatschneider, C. (2017). Factor structure and aetiological architecture of the BRIEF: A twin study. *Journal of Neuropsychology, 11*(2), 252-276. doi:10.1111/jnp.12084
- Logan, G. D., & Cowan, W. B. (1984). On the ability to inhibit thought and action: A theory of an act of control. *Psychological Review, 91*, 295 - 327.
- Logan, G. D., Schachar, R. J., & Tannock, R. (1997). Impulsivity and inhibitory control. *Psychological Science, 8*, 60 - 64.

- Lu, C. H., & Proctor, R. W. (1995). The influence of irrelevant location information on performance: A review of the Simon and spatial Stroop effects. *Psychonomic Bulletin & Review*, 2, 174 - 207. doi:10.3758/bf03210959
- Luna, B., Marek, S., Larsen, B., Tervo-Clemmens, B., & Chahal, R. (2015). An integrative model of the maturation of cognitive control. In S. E. Hyman (Ed.), *Annual Review of Neuroscience* (Vol. 38, pp. 151-170).
- MacCallum, R. C., & Austin, J. T. (2000). Applications of structural equation modeling in psychological research. *Annu Rev Psychol*, 51, 201-226. doi:10.1146/annurev.psych.51.1.201
- MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological methods*, 1, 130-149.
- MacLeod, C. M. (1991). Half a century of research on the Stroop effect: An integrative review. *Psychological Bulletin*, 109, 163 - 203.
- Mahone, E. M., Cirino, P. T., Cutting, L. E., Cerrone, P. M., Hagelthorn, K. M., Hiemenz, J. R., . . . Denckla, M. B. (2002). Validity of the behavior rating inventory of executive function in children with ADHD and/or Tourette syndrome. *Archives of Clinical Neuropsychology*, 17(7), 643-662. doi:[https://doi.org/10.1016/S0887-6177\(01\)00168-8](https://doi.org/10.1016/S0887-6177(01)00168-8)
- Marsh, H. W., Hau, K. T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. *Structural equation modeling*, 11(3), 320-341. doi:https://doi.org/10.1207/s15328007sem1103_2
- Marsh, H. W., Lüdtke, O., Nagengast, B., Morin, A. J. S., & Von Davier, M. (2013). Why item parcels are (almost) never appropriate: Two wrongs do not make a right—Camouflaging misspecification with item parcels in CFA models. *Psychological methods*, 18(3), 257 - 284. doi:<http://dx.doi.org/10.1037/a0032773>
- McAuley, T., & White, D. (2011). A latent variables examination of processing speed, response inhibition, and working memory during typical development. *Journal of Experimental Child Psychology*, 108, 453-468. doi:10.1016/j.jecp.2010.08.009

- McCabe, D. P., Roediger, H. L., McDaniel, M. A., Balota, D. A., & Hambrick, D. Z. (2010). The relationship Between working memory capacity and executive functioning: Evidence for a common executive attention construct. *Neuropsychology, 24*, 222 - 243. doi:10.1037/a0017619
- McDonald, R. P., & Ho, M. H. (2002). Principles and practice in reporting structural equation analyses. *Psychol Methods, 7*, 64 - 82. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/11928891>
- McRae, K., Jacobs, S. E., Ray, R. D., John, O. P., & Gross, J. J. (2012). Individual differences in reappraisal ability: Links to reappraisal frequency, well-being, and cognitive control. *Journal of Research in Personality, 46*, 2 - 7. doi:10.1016/j.jrp.2011.10.003
- Menon, V., Adleman, N. E., White, C. D., Glover, G. H., & Reiss, A. L. (2001). Error-related brain activation during a Go/NoGo response inhibition task. *Human Brain Mapping, 12*, 131 - 143.
- Miyake, A., & Friedman, N. P. (2012). The nature and organization of individual differences in executive functions: Four general conclusions. *Current Directions In Psychological Science, 21*, 8-14. doi:10.1177/0963721411429458
- Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "Frontal Lobe" tasks: A latent variable analysis. *Cognitive psychology, 41*, 49-100. doi:10.1006/cogp.1999.0734
- Muris, P., van der Pennen, E., Sigmond, R., & Mayer, B. (2008). Symptoms of anxiety, depression, and aggression in non-clinical children: relationships with self-report and performance-based measures of attention and effortful control. *Child Psychiatry Hum Dev, 39*(4), 455-467. doi:10.1007/s10578-008-0101-1
- Murray, K. T., & Kochanska, G. (2002). Effortful control: Factor structure and relation to externalizing and internalizing behaviors. *Journal of Abnormal Child Psychology, 30*, 503 - 514. doi:Unsp 0091-0627/02/1000-0503/0
10.1023/a:1019821031523
- Muthén, B., du Toit, S. H. C., & Spisic, D. (1997). Robust inference using weighted least squares and quadratic estimating equations in latent variable modeling with

categorical and continuous outcomes. *Conditionally accepted for publication in Psychometrika*.

Muthén, L. K., & Muthén, B. O. (1998 - 2012). *Mplus user's guide*. (Seventh ed.). Los Angeles, CA: Muthén & Muthén.

Nigg, J. T. (2017). Annual Research Review: On the relations among self-regulation, self-control, executive functioning, effortful control, cognitive control, impulsivity, risk-taking, and inhibition for developmental psychopathology. *J Child Psychol Psychiatry*, 58(4), 361-383. doi:10.1111/jcpp.12675

Nigg, J. T., Willcutt, E. G., Doyle, A. E., & Sonuga-Barke, E. J. (2005). Causal heterogeneity in attention-deficit/hyperactivity disorder: do we need neuropsychologically impaired subtypes? *Biol Psychiatry*, 57(11), 1224-1230. doi:10.1016/j.biopsych.2004.08.025

Nisbett, R. E., Aronson, J., Blair, C., Dickens, W., Flynn, J., Halpern, D. F., & Turkheimer, E. (2012). Intelligence: New findings and theoretical developments. *American Psychologist*, 67, 130 - 159. doi:10.1037/a0026699

Nyberg, L., Brocki, K., Tillman, C., & Bohlin, G. (2009). The proposed interaction between working memory and inhibition. *European Journal of Cognitive Psychology*, 21, 84 - 111.

Ochsner, K. N., & Gross, J. J. (2005). The cognitive control of emotion. *Trends in Cognitive Sciences*, 9, 242 - 249.

Oosterlaan, J., & Sergeant, J. A. (1996). Inhibition in ADHD, aggressive, and anxious children: A biologically based model of child psychopathology. *Journal of Abnormal Child Psychology*, 24, 19 - 36. doi:10.1007/bf01448371

Pe, M. L., Raes, F., & Kuppens, P. (2013). The cognitive building blocks of emotion regulation: Ability to update working memory moderates the efficacy of rumination and reappraisal on emotion. *PLoS One*, 8. doi:10.1371/journal.pone.0069071

Peirce, J. W. (2007). PsychoPy - psychophysics software in Python. *Journal of Neuroscience Methods*, 162, 8-13.

Peirce, J. W. (2008). Generating stimuli for neuroscience using PsychoPy. *Frontiers in neuroinformatics*, 2, 10 doi:10.3389/neuro.11.010.2008

- Petersen, S. E., & Posner, M. I. (2012). The attention system of the human brain: 20 years after. *Annual Review of Neuroscience*, *35*, 73 - 89. doi:10.1146/annurev-neuro-062111-150525
- Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of Method Bias in Social Science Research and Recommendations on How to Control It. In S. T. Fiske, D. L. Schacter, & S. E. Taylor (Eds.), *Annual Review of Psychology*, Vol 63 (Vol. 63, pp. 539-569).
- Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience*, *13*, 25-42. doi:10.1146/annurev.ne.13.030190.000325
- Posner, M. I., & Rothbart, M. K. (2009). Toward a physical basis of attention and self regulation. *Physics of life reviews*, *6*, 103-120. doi:10.1016/j.plprev.2009.02.001
- Posner, M. I., Rothbart, M. K., Vizueta, N., Levy, K. N., Evans, D. E., Thomas, K. M., & Clarkin, J. F. (2002). Attentional mechanisms of borderline personality disorder. *Proceedings of the National Academy of Sciences of the United States of America*, *99*, 16366 - 16370. doi:10.1073/pnas.252644699
- Putnam, S. P., Ellis, L. K., & Rothbart, M. K. (2001). *The structure of temperament from infancy through adolescence*. Paper presented at the Advances/proceedings in research on temperament., (pp. 165 – 182). Germany: Pabst Scientific.
- Redick, T. S., & Engle, R. W. (2006). Working memory capacity and attention network test performance. *Applied Cognitive Psychology*, *20*, 713 - 721. doi:10.1002/acp.1224
- Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research*, *47*(5), 667 - 696.
doi:<https://doi.org/10.1080/00273171.2012.715555>
- Reise, S. P., Scheines, R., Widaman, K. F., & Haviland, M. G. (2013). Multidimensionality and structural coefficient bias in structural equation modeling a bifactor perspective. *Educational and Psychological Measurement*, *73*(1), 5 - 26.
doi:<https://doi.org/10.1177/0013164412449831>
- Repovs, G., & Baddeley, A. (2006). The multi-component model of working memory: Explorations in experimental cognitive psychology. *Neuroscience*, *139*, 5 - 21. doi:10.1016/j.neuroscience.2005.12.061

- Roberts Jr, R. J., & Pennington, B. F. (1996). An interactive framework for examining prefrontal cognitive processes. *Developmental Neuropsychology*, *12*, 105 - 126. doi:10.1080/87565649609540642
- Rodriguez, A., Reise, S. P., & Haviland, M. G. (2016b). Evaluating bifactor models: Calculating and interpreting statistical indices. *Psychological methods*, *21*(2), 137-150. doi:<http://dx.doi.org/10.1037/met0000045>
- Rothbart, M. K., & Bates, J. E. (2006). Temperament in children's development. In W. Damon, R. Lerner, & N. Eisenberg (Eds.), *Handbook of child psychology* (Vol. 3 Social, emotional, and personality development, pp. 99 - 166). New York: Wiley.
- Rothbart, M. K., & Derryberry, D. (1981). Development of individual differences in temperament. In M. E. Lamb & A. L. Brown (Eds.), *Advances in developmental psychology* (Vol. 1, pp. 37 - 86). Hillsdale, NJ.: Erlbaum.
- Rothbart, M. K., Ellis, L. K., Rueda, M. R., & Posner, M. I. (2003). Developing mechanisms of temperamental effortful control. *Journal of Personality*, *71*, 1113 - 1143. doi:10.1111/1467-6494.7106009
- Rothbart, M. K., & Gartstein, M. A. (2008). Temperament. In M. H. Editors-in-Chief: Marshall & B. B. Janette (Eds.), *Encyclopedia of Infant and Early Childhood Development* (pp. 318-332). San Diego: Academic Press.
- Rothbart, M. K., Sheese, B. E., & Posner, M. I. (2007). Executive attention and effortful control: Linking temperament, brain networks, and genes. *Child Development Perspectives*, *1*, 2-7. doi:10.1111/j.1750-8606.2007.00002.x
- Rueda, M. R., Fan, J., McCandliss, B. D., Halparin, J. D., Gruber, D. B., Lercari, L. P., & Posner, M. I. (2004). Development of attentional networks in childhood. *Neuropsychologia*, *42*(8), 1029-1040. doi:10.1016/j.neuropsychologia.2003.12.012
- Rueda, M. R., Posner, M. I., & Rothbart, M. K. (2004). Attentional control and self-regulation. In R. F. Baumeister & K. D. Vohs (Eds.), *Handbook of self-regulation: Research, theory, and applications*. (pp. 283-300). New York: The Guilford Press.
- Rueda, M. R., Posner, M. I., & Rothbart, M. K. (2005). The development of executive attention: Contributions to the emergence of self-regulation. *Developmental Neuropsychology*, *28*, 573-594. doi:10.1207/s15326942dn2802_2

- Rueda, M. R., Posner, M. I., & Rothbart, M. K. (2011). Attentional control and self-regulation. In K. D. Vohs & R. F. Baumeister (Eds.), *Handbook of self-regulation: Research, theory, and applications* (2nd ed., pp. 284 - 299). New York: The Guilford Press.
- Rueda, M. R., Pozuelos, J. P., & Combita, L. M. (2015). Cognitive neuroscience of attention: From brain mechanisms to individual differences in efficiency. *AIMS Neuroscience*, 2, 183 - 202.
- Samyn, V., Roeyers, H., Bijttebier, P., Rosseel, Y., & Wiersema, J. R. (2015). Assessing effortful control in typical and atypical development: Are questionnaires and neuropsychological measures interchangeable? A latent-variable analysis. *Research in Developmental Disabilities*, 36, 587-599. doi:10.1016/j.ridd.2014.10.018
- Sattler, J. M. (2008). *Resource guide to accompany assessment of children: Cognitive foundations*. San Diego: Jerome M. Sattler, Publisher, Inc.
- Schmeichel, B. J., Volokhov, R. N., & Demaree, H. A. (2008). Working memory capacity and the self-regulation of emotional expression and experience. *Journal of Personality and Social Psychology*, 95, 1526 - 1540.
- Schmiedek, F., Hildebrandt, A., Lövdén, M., Wilhelm, O., & Lindenberger, U. (2009). Complex span versus updating tasks of working memory: The gap is not that deep. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 35, 1089 - 1096. doi:10.1037/a0015730
- Shipstead, Z., Harrison, T. L., & Engle, R. W. (2016). Working Memory Capacity and Fluid Intelligence: Maintenance and Disengagement. *Perspectives on Psychological Science*, 11(6), 771-799. doi:10.1177/1745691616650647
- Shipstead, Z., Lindsey, D. R. B., Marshall, R. L., & Engle, R. W. (2014). The mechanisms of working memory capacity: Primary memory, secondary memory, and attention control. *Journal of Memory and Language*, 72, 116-141.
doi:<https://doi.org/10.1016/j.jml.2014.01.004>
- Simmonds, D. J., Pekar, J. J., & Mostofsky, S. H. (2008). Meta-analysis of Go/No-go tasks demonstrating that fMRI activation associated with response inhibition is task-dependent. *Neuropsychologia*, 46, 224 - 232.
doi:10.1016/j.neuropsychologia.2007.07.015

- Simonds, J., Kieras, J. E., Rueda, M. R., & Rothbart, M. K. (2007). Effortful control, executive attention, and emotional regulation in 7–10-year-old children. *Cognitive Development, 22*, 474-488.
- Skrondal, A., & Laake, P. (2001). Regression among factor scores. *psychometrika, 66*(4), 563-575. doi:<https://doi.org/10.1007/BF02296196>
- Small, N. (1980). Marginal skewness and kurtosis in testing multivariate normality. *Applied Statistics, 85-87*.
- Snyder, H. R., Gulley, L. D., Bijttebier, P., Hartman, C. A., Oldehinkel, A. J., Mezulis, A., . . . Hankin, B. L. (2015). Adolescent emotionality and effortful control: Core latent constructs and links to psychopathology and functioning. *Journal of Personality and Social Psychology, 109*, 1132 - 1149. doi:10.1037/pspp0000047
- Snyder, H. R., Miyake, A., & Hankin, B. L. (2015). Advancing understanding of executive function impairments and psychopathology: Bridging the gap between clinical and cognitive approaches. *Frontiers in Psychology, 6*. doi:10.3389/fpsyg.2015.00328
- Sonuga-Barke, E. J. S. (2003). The dual pathway model of AD/HD: An elaboration of neuro-developmental characteristics. *Neuroscience & biobehavioral reviews, 27*(7), 593-604. doi:<https://doi.org/10.1016/j.neubiorev.2003.08.005>
- Sparkes, S. J. (2006). *The influence of ADHD and experimental context on components of attention in children (Doctoral dissertation)*. Dalhousie University. Dissertation Abstracts International, 67, 6747.
- Strauss, M. E., & Smith, G. T. (2009). Construct Validity: Advances in Theory and Methodology. *Annual Review of Clinical Psychology, 5*, 1-25. doi:10.1146/annurev.clinpsy.032408.153639
- Streiner, D. L. (2003). Starting at the beginning: An introduction to coefficient alpha and internal consistency. *Journal of Personality Assessment, 80*, 99-103. doi:10.1207/s15327752jpa8001_18
- Taasoobshirazi, G., & Wang, S. (2016). The performance of the SRMR, RMSEA, CFI, and TLI: An examination of sample size, path size, and degrees of freedom. *Journal of Applied Quantitative Methods, 11*(3), 31-39.
- Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics*. (6th ed.). Boston: Pearson Education, Inc.

- Tellegen, A., & Briggs, P. F. (1967). Old wine in new skins: Grouping Wechsler subtests into new scales. *Journal of consulting psychology, 31*, 499 - 506.
- Ten Eycke, K. D., & Dewey, D. (2016). Parent-report and performance-based measures of executive function assess different constructs. *Child Neuropsychology, 22*(8), 889-906. doi:10.1080/09297049.2015.1065961
- Tiego, J., Testa, R., Bellgrove, M. A., Pantelis, C., & Whittle, S. (2018). A hierarchical model of inhibitory control. *Frontiers in Psychology, 9*(1339). doi:10.3389/fpsyg.2018.01339
- Tomarken, A. J., & Waller, N. G. (2005). Structural equation modeling: Strengths, limitations, and misconceptions. *Annu Rev Clin Psychol, 1*, 31-65. doi:10.1146/annurev.clinpsy.1.102803.144239
- Toplak, M. E., Bucciarelli, S. M., Jain, U., & Tannock, R. (2008). Executive Functions: Performance-Based Measures and the Behavior Rating Inventory of Executive Function (BRIEF) in Adolescents with Attention Deficit/Hyperactivity Disorder (ADHD). *Child Neuropsychology, 15*(1), 53-72. doi:10.1080/09297040802070929
- Toplak, M. E., West, R. F., & Stanovich, K. E. (2013). Practitioner Review: Do performance-based measures and ratings of executive function assess the same construct? *Journal of Child Psychology and Psychiatry, 54*, 131 - 143. doi:10.1111/jcpp.12001
- Unsworth, N., Schrock, J. C., & Engle, R. W. (2004). Working memory capacity and the antisaccade task: Individual differences in voluntary saccade control. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 30*, 1302 - 1321. doi:10.1037/0278-7393.30.6.1302
- Unsworth, N., & Spillers, G. J. (2010). Working memory capacity: Attention control, secondary memory, or both? A direct test of the dual-component model. *Journal of Memory and Language, 62*, 392 - 406. doi:10.1016/j.jml.2010.02.001
- Verbruggen, F., & Logan, G. D. (2009). Models of response inhibition in the stop-signal and stop-change paradigms. *Neuroscience and Biobehavioral Reviews, 33*, 647-661. doi:10.1016/j.neubiorev.2008.08.014
- Verbruggen, F., Logan, G. D., & Stevens, M. A. (2008). STOP-IT: Windows executable software for the stop-signal paradigm. *Behavior Research Methods, 40*, 479-483.

- Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems of p-values. *Psychonomic Bulletin & Review*, *14*(5), 779-804. doi:10.3758/bf03194105
- Wechsler, D. (2003a). *Wechsler Intelligence Scale for Children - Fourth Edition: Administration and scoring manual*. San Antonio: The Psychological Corporation.
- Wechsler, D. (2003b). *Wechsler Intelligence Scale for Children - Fourth Edition: Technical and interpretive manual*. San Antonio: The Psychological Corporation.
- Wiebe, S. A., Espy, K. A., & Charak, D. (2008). Using confirmatory factor analysis to understand executive control in preschool children: I. Latent structure. *Developmental Psychology*, *44*, 575-587.
- Wiedermann, W., & von Eye, A. (2015). Direction of effects in mediation analysis. *Psychol Methods*, *20*(2), 221-244. doi:10.1037/met0000027
- Wilhelm, O., Hildebrandt, A. H., & Oberauer, K. (2013). What is working memory capacity, and how can we measure it? *Frontiers in Psychology*, *4*, 1 - 22. doi:10.3389/fpsyg.2013.00433
- Willcutt, E. G., Doyle, A. E., Nigg, J. T., Faraone, S. V., & Pennington, B. F. (2005). Validity of the Executive Function Theory of Attention-Deficit/Hyperactivity Disorder: A Meta-Analytic Review. *Biological Psychiatry*, *57*(11), 1336-1346. doi:<https://doi.org/10.1016/j.biopsych.2005.02.006>
- Williams, B. R., Ponesse, J. S., Schachar, R. J., Logan, G. D., & Tannock, R. (1999). Development of inhibitory control across the life span. *Developmental Psychology*, *35*, 205 - 213.
- Yu, J., Kam, C., & Lee, T. M. (2016). Better working memory and motor inhibition in children who delayed gratification. *Frontiers in Psychology*, *7*, 1 - 7. doi:10.3389/fpsyg.2016.01098
- Zelazo, P. D., & Cunningham, W. A. (2007). Executive function: Mechanisms underlying emotion regulation. In J. J. Gross (Ed.), *Handbook of emotion regulation*. (pp. 135 - 158). New York: The Guilford Press.
- Zhou, Q., Chen, S. H., & Main, A. (2012). Commonalities and differences in the research on children's effortful control and executive function: A call for an integrated model of self-regulation. *Child Development Perspectives*, *6*, 112 - 121. doi:10.1111/j.1750-8606.2011.00176.x

Table 1

Summary of Fit Statistics for Competing Confirmatory Factor Analysis Models of the BRIEF

	Model	<i>df</i>	χ^2	<i>P</i>	RMSEA (90% <i>CI</i>)	SRMR	CFI	AIC	BIC	$Pr_{BIC}(H_0 D)$
1	Three-Factor ¹	23	34.901	.150	.064 (.000 - .104)	.036	.987	5399.042	5487.455	.414
2	Two-Factor ¹	25	43.913	.058	.077 (.037 - .114)	.038	.979	5404.053	5486.762	.586
3	One-Factor ²	24	79.915	<.001	.135 (.103 - .168)	.063	.939	5442.056	5527.616	<.001
4	Bi-Factor ³	18	33.718	.037	.083 (.037 - .125)	.022	.983	5407.859	5510.532	<.001

Note. *df* = Degrees of freedom; χ^2 = Chi square value for test of model fit using full information maximum likelihood estimation; *p* = significance value of the chi square test statistic; RMSEA = Root mean square error of approximation; *CI* = Confidence interval; SRMR = Standardized root mean residual.

¹ Model included an estimated error covariance between the working memory and inhibit scales.

² Included three, freely estimated error covariances.

³All scales loaded significantly on the general EF factor however, none of the secondary loadings on the metacognition or emotional and behavioral regulation group factors were statistically significant.

Table 2

Summary of Fit Statistics for Competing Confirmatory Factor Analysis Models of the EATQ-R Parent- and Self-Report Forms

	Model	<i>df</i>	χ^2	<i>P</i>	RMSEA (90%CI)	WRMR	CFI
Parent-Report							
1	Three-Factor	132	235.098	<.001	.078 (.062 - .094)	.843	.970
2	Two-Factor ¹	120	152.894	.023	.046 (.018 - .067)	.609	.991
3	One-Factor ¹	118	147.657	.034	.044 (.013 - .065)	.600	.991
4	Bi-Factor ¹	118	144.100	.052	.042 (.000 - .063)	.582	.992
Self-Report							
1	Two-Factor ¹	90	111.432	.058	.043 (.000 - .067)	.651	.978
2	One-Factor ¹	89	111.855	.051	.045 (.000 - .069)	.652	.977
3	Bi-Factor ¹	88	108.579	.068	.043 (.000 - .067)	.631	.979

Note. *df* = Degrees of freedom; χ^2 = Chi square value for test of model fit using WLSMV estimator; *p* = significance value of the chi square test statistic; RMSEA = Root mean square error of approximation; *CI* = Confidence interval; WRMR = Weighted root mean residual.

¹ Model included freely estimated error covariances, all significant at *p* < .05 when corrected for multiple *post hoc* comparisons (B-H FDR *q* = .05).

Table 3

Summary of Fit Statistics for Competing Confirmatory Factor Analysis Models of Executive Attention

	Model	<i>df</i>	χ^2	<i>p</i>	RMSEA (90% <i>CI</i>)	SRMR	CFI	AIC	BIC	Pr _{BIC} (<i>H</i> ₁ <i>D</i>)
1	Three-Factor ¹	23	35.394	.150	.063 (.007 - .102)	.048	.952	4471.743	4562.035	.011
2	Two-Factor ¹	25	38.776	.133	.064 (.037 - .114)	.050	.947	4471.125	4555.592	.263
3	One-Factor ^{1,2}	25	36.748	.189	.059 (.000 - .097)	.048	.955	4469.097	4553.564	.726

Note. *df* = Degrees of freedom; χ^2 = Chi square value for test of model fit using full information maximum likelihood estimation; *p* = significance value of the chi square test statistic; RMSEA = Root mean square error of approximation; *CI* = Confidence interval; SRMR = Standardized root mean residual.

¹ Included a freely estimated error covariance between SSRT and symbol search.

² Included a freely estimated error covariance between SSRT and no-go commission errors.

Table 4

Intercorrelations Amongst the Executive Attention, BRIEF, EATQ-R, and CBCL Variables

	1	2	3	4	5
1. Executive Attention Factor Score Estimates					
2. BRIEF Metacognition	-.510				
3. BRIEF Emotional & Behavioral Regulation	-.362	.699			
4. EATQ-R Effortful Control Parent-Report	.450	-.884	-.669		
5. EATQ-R Effortful Control Self-Report	.340	-.664	-.452	.666	
6. CBCL DSM ADHD Problems Scale	-.368	.720	.726	-.770	-.550

Note. All parameters were significant at $p < .001$.

Figure 1. Two-factor model of executive function using the BRIEF clinical scale raw scores with the monitoring scale separated into task monitoring and self-monitoring subscales.

Note. Model fit statistics were: ($\chi^2(25) = 43.913, p = .058$; RMSEA = .077 (90%CI=.037, .114); CFI = .979; SRMR = .038). Initiate = Initiate scale; TaskMon = Task monitoring subscale; Plan = Plan/organize scale; Organize = Organization of materials age-residualized scale; WM = Working memory scale; SelfMon = Self-monitoring subscale; Control = Emotional control scale. Fully standardized estimates are in bold typeface. Unstandardized estimates appear below with bootstrapped (10,000 posterior draws) standard errors in brackets. All parameters were significant at $p < .001$ unless otherwise indicated. ****** $p < .01$.

Figure 2. Bifactor model of EC modeled from data obtained on the EATQ-R parent-report form.

Note. Model fit statistics were: ($\chi^2(118) = 144.100, p = .052$, RMSEA = .042 [90%CI=.000, .063], CFI = .992, WRMR = .582).

Parameters estimates are fully standardized. All parameters significant at $p < .001$ unless otherwise indicated. ****** $p < .01$; * $p < .05$. All error covariances were statistically significant (Benjamini-Hochberg $p = .049$) when adjusted for multiple *post hoc* comparisons (B-H FDR $q = .05$). $n = 134$.

Figure 3. One-factor model of EC modeled from data obtained on the EATQ-R self-report form.

Note. Model fit statistics were: ($\chi^2(89) = 111.855, p = .051, RMSEA = .045$ [90%CI = .000, .069], CFI = .977, WRMR = .652).

Parameters estimates are fully standardized. All parameters significant at $p < .001$ unless otherwise indicated. ** $p < .01$; * $p < .05$. All error covariances were statistically significant (Benjamini-Hochberg $p = .049$) when adjusted for multiple *post hoc* comparisons (B-H FDR $q = .05$). $n = 128$.

Figure 4. Unitary executive attention model consisting of a single latent variable predicting performance on measures of working memory capacity, psychometric *g*, and response inhibition.

Note. Model fit statistics were: ($\chi^2(25) = 36.748, p = .189, RMSEA = .059$ [90%CI = .000, .097], CFI = .955, SRMR = .048). LR = Listening recall; CR = Counting recall; BDR = Backwards digit recall; VC = Vocabulary; MR = Matrix reasoning; SS = Symbol search; SSRT = Stop signal reaction time age-residualized; No-Go = Commission errors on no-go trials; Simon = Simon task stimulus-response conflict. Fully standardized estimates are in bold typeface. Unstandardized estimates appear below with bootstrapped (10,000 posterior draws) standard errors in brackets. All parameters were significant at $p < .001$ unless otherwise indicated. ** $p < .01$; * $p < .05$.

Figure 5. Empirical relationships between executive function and effortful control as measured by behavioral ratings on the BRIEF and EATQ-R.

Note: Model fit statistics were: ($\chi^2(1) = .690, p = .448, RMSEA = .000$ [90%CI = .000, .213], CFI = 1.000, SRMR = .010). MCI = Metacognition; EBR = Emotional and behavioral regulation; EC-PR = Effortful control parent-report; EC-SR = Effortful control self-report. EAFSE = Executive attention factor score estimates. Fully standardized estimates are in bold typeface. Unstandardized estimates appear below with bootstrapped (10,000 posterior draws) standard errors in brackets. All parameters were significant at $p < .001$ unless otherwise indicated. ** $p < .01$; ^ $p > .05$. The estimate of residual variance for the MCI variable was not significant ($p > .05$).

Figure 6. A unitary self-regulation factor with loadings from the BRIEF, and EATQ-R self- and parent-report.

Note: Model fit statistics were: ($\chi^2(2) = 1.774, p = .422, RMSEA = .000$ [90%CI = .000, .165], CFI = 1.000, SRMR = .015).

MC = Metacognition; EBR = Emotional and behavioral regulation; EC-PR = Effortful control parent-report; EC-SR = Effortful control self-report. Fully standardized estimates are in bold typeface. Unstandardized estimates appear below with bootstrapped (10,000 posterior draws) standard errors in brackets. All parameters were significant at $p < .001$ unless otherwise indicated. * $p < .05$.

Figure 7. Self-regulation factor regressed onto the executive attention factor.

Note: Model fit statistics were: ($\chi^2(5) = 3.980, p = .617, RMSEA = .000$ [90%CI = .000, .106], CFI = 1.000, SRMR = .016).

EAFSE = Executive attention factor score estimates; MC = Metacognition; EBR = Emotional and behavioral regulation; EC-PR = Effortful control parent-report; EC-SR = Effortful control self-report. Fully standardized estimates are in bold typeface. Unstandardized estimates appear below with bootstrapped (10,000 posterior draws) standard errors in brackets. All parameters were significant at $p < .001$ unless otherwise indicated. * $p < .05$.

Figure 8. Model of ADHD problems regressed onto the self-regulation factor, with variance indirectly explained by executive attention.

Note. Model fit statistics were: ($\chi^2(8) = 11.448, p = .197, RMSEA = .056$ [90%CI = .000, .124], CFI = .994, SRMR = .018).

EAFSE = Executive attention factor score estimates. MC = Metacognition; EBR = Emotional and behavioral regulation; EC-PR = Effortful control parent-report; EC-SR = Effortful control self-report. CBCL ADHD = CBCL/6-18 DSM-orientated ADHD problems scale summed score.

Error covariance between EBR and ADHD problems ($\theta\epsilon = .236, p < .001$) has been omitted for clarity. Fully standardized estimates are in bold typeface. Unstandardized estimates appear below with bootstrapped (10,000 posterior draws) standard errors in brackets. All parameters were significant at $p < .001$. The indirect effect of executive attention on ADHD problems was statistically significant ($\beta = -.462, p < .001; b = -1.498$ [95%CI = -1.041, -2.028], $p < .001$), explaining 21.3% of the variance.

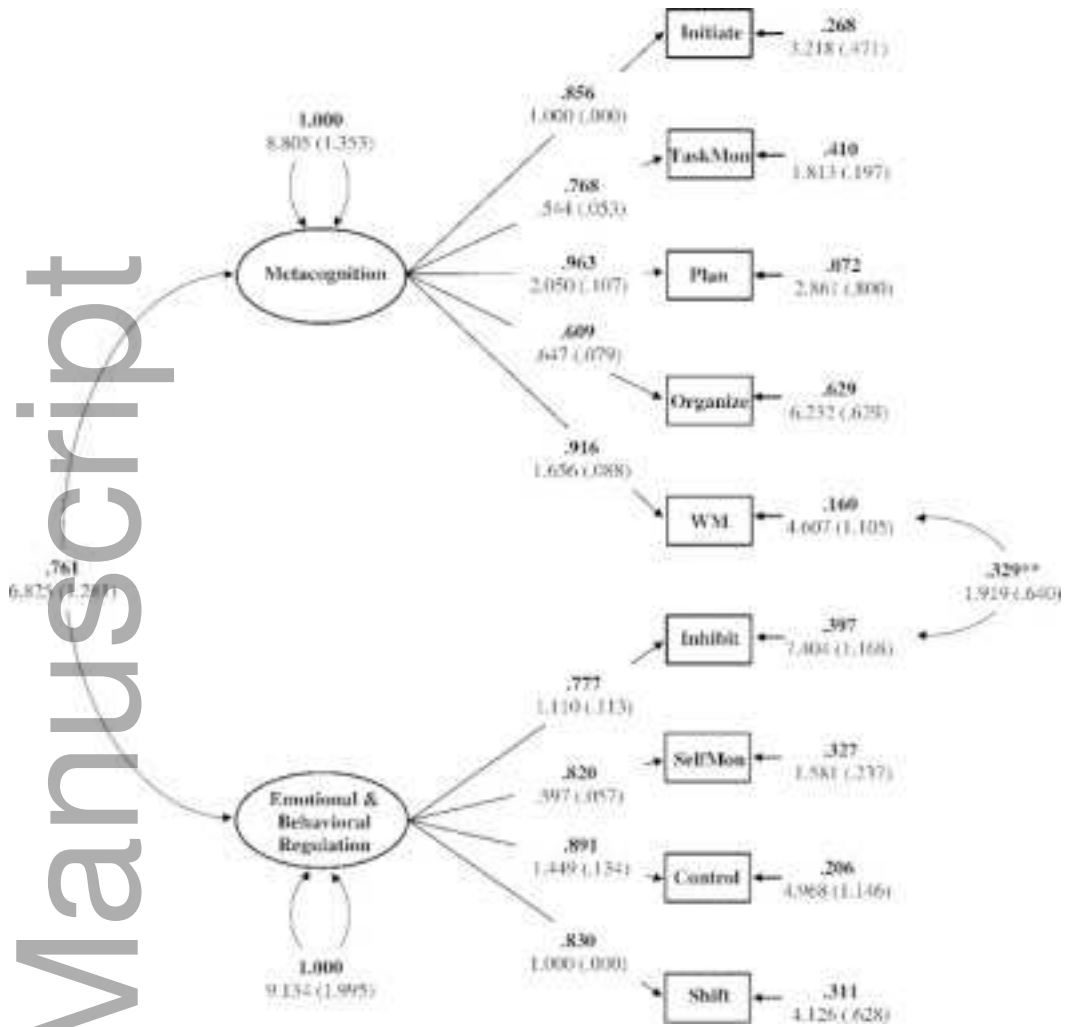
Figure 9. Model of self-regulation and ADHD problems regressed onto executive attention.

Note. Model fit statistics were: ($\chi^2(7) = 10.517, p = .170, RMSEA = .061$ [90%CI = .000, .131], CFI = .993, SRMR = .016).

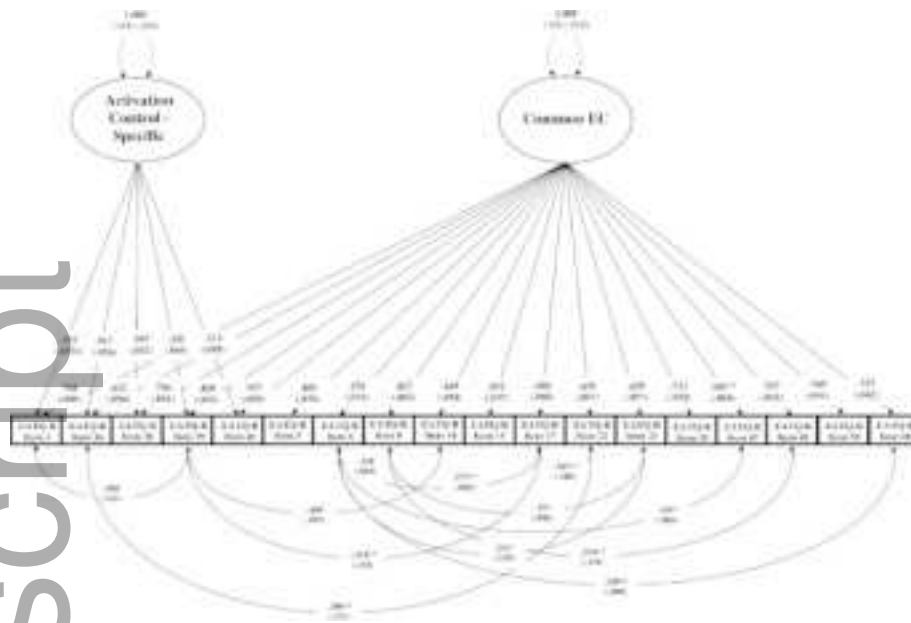
EAFSE = Executive attention factor score estimates. MC = Metacognition; EBR = Emotional and behavioral regulation; EC-PR = Effortful control parent-report; EC-SR = Effortful control self-report. CBCL ADHD = CBCL/6-18 DSM-orientated ADHD problems scale summed score.

Error covariance between EBR and ADHD problems ($\theta_{\epsilon} = .259, p < .001$) has been omitted for clarity. Fully standardized estimates are in bold typeface. Unstandardized estimates appear below with bootstrapped (10,000 posterior draws) standard errors in brackets. All parameters were significant at $p < .001$.

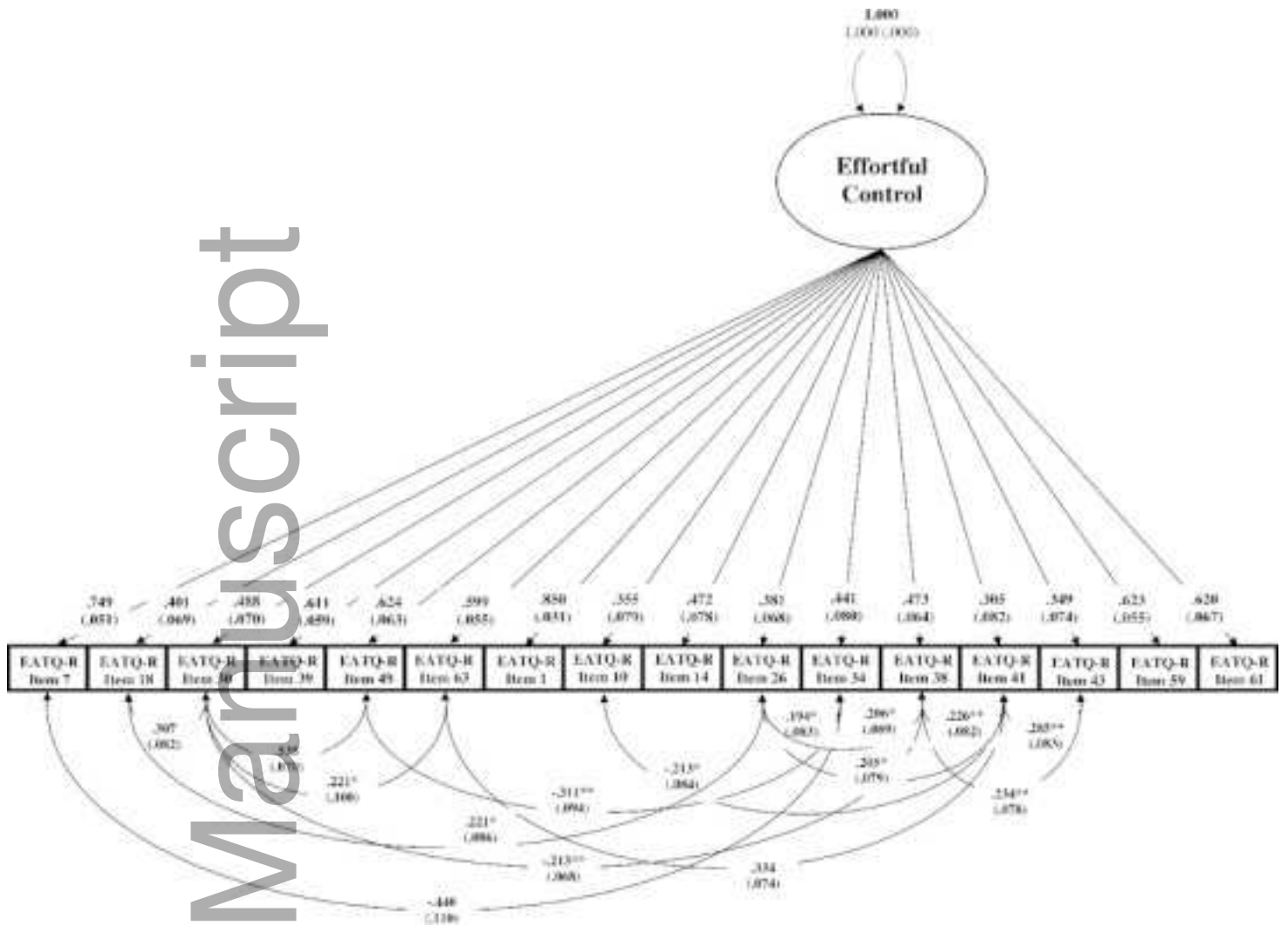
Author Manuscript



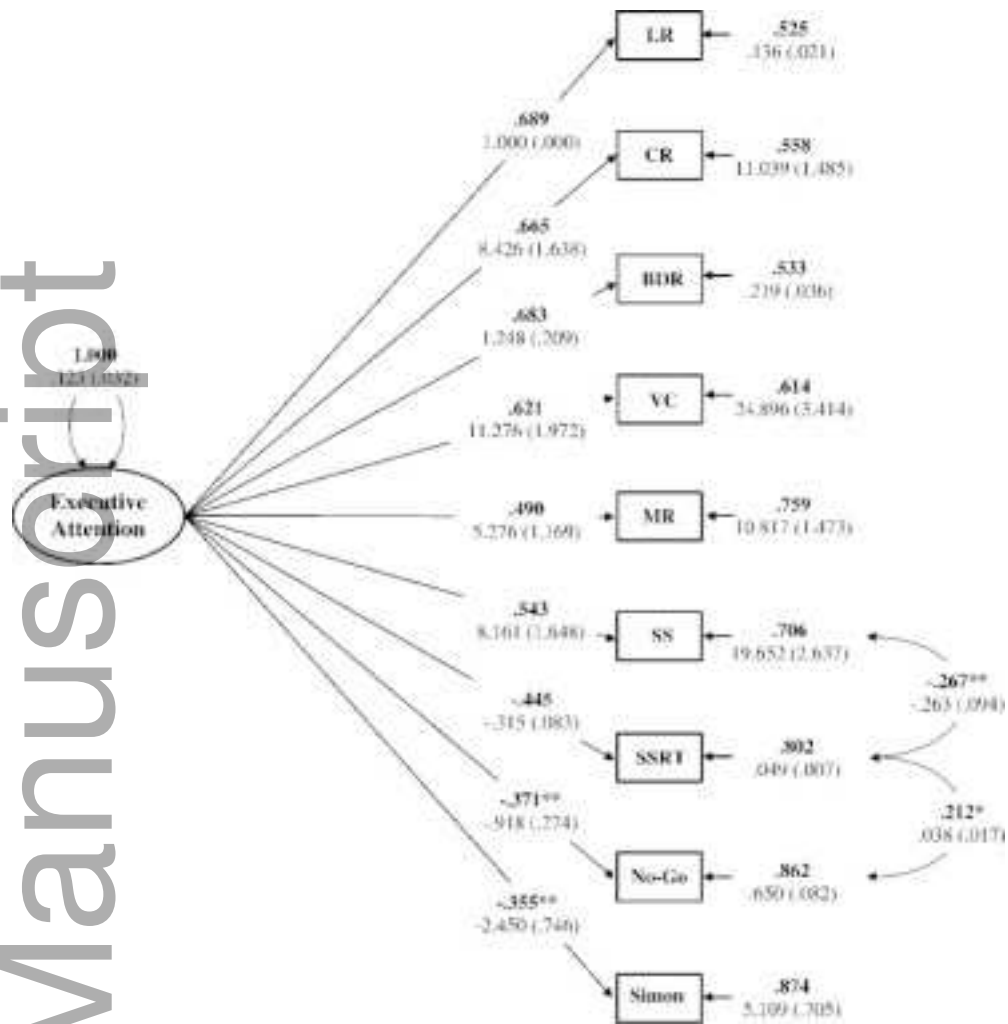
desc_12918_f1.tiff



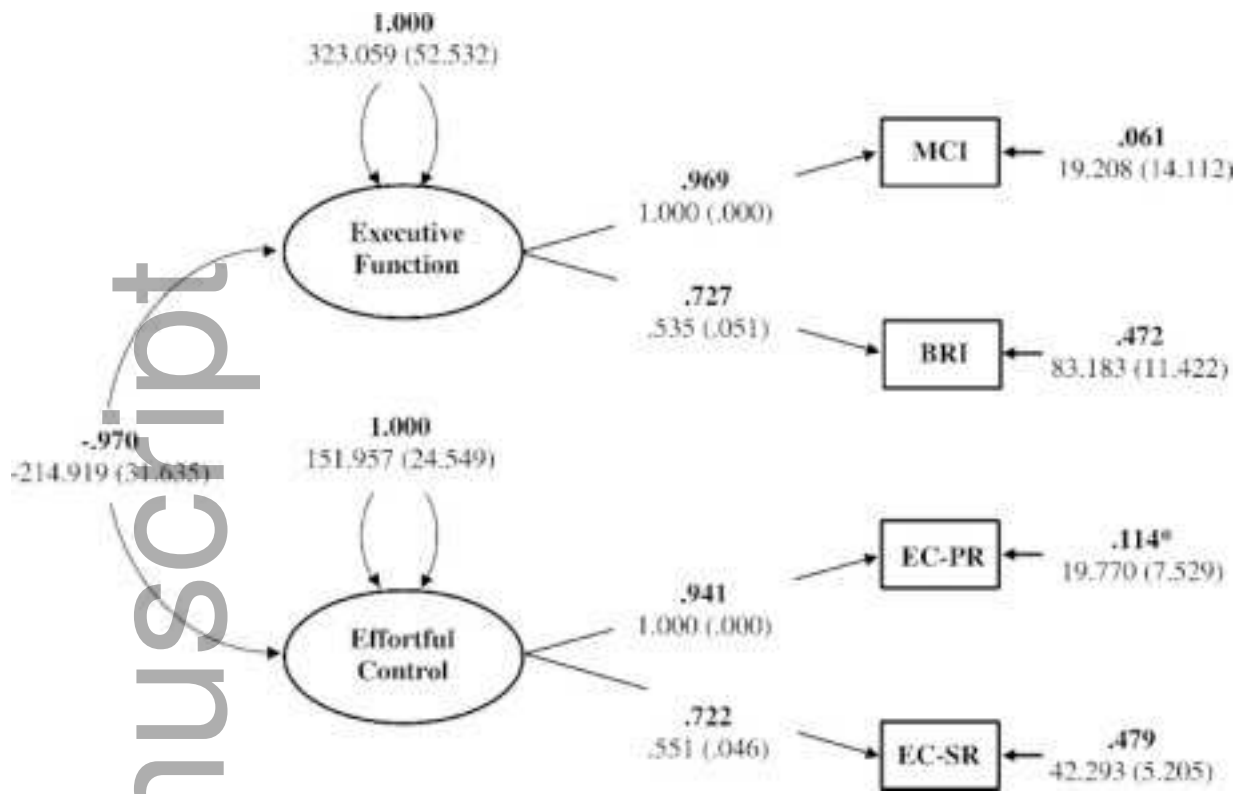
desc_12918_f2.tiff



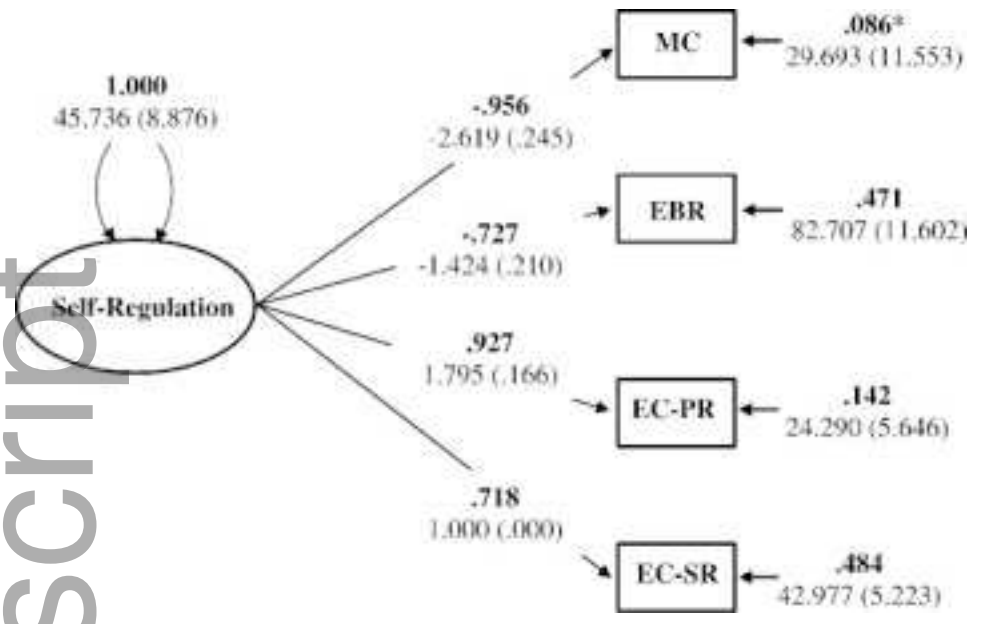
desc_12918_f3.tiff



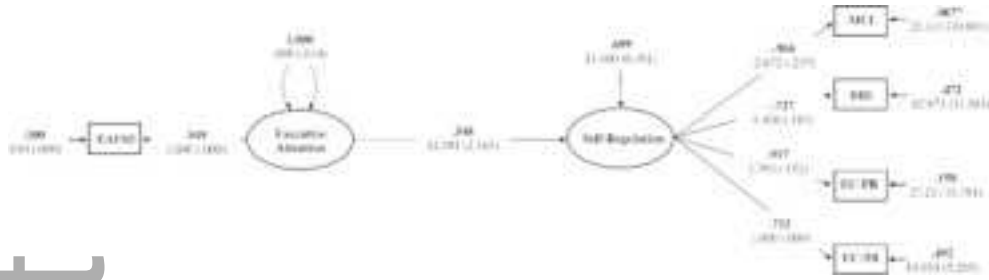
desc_12918_f4.tiff



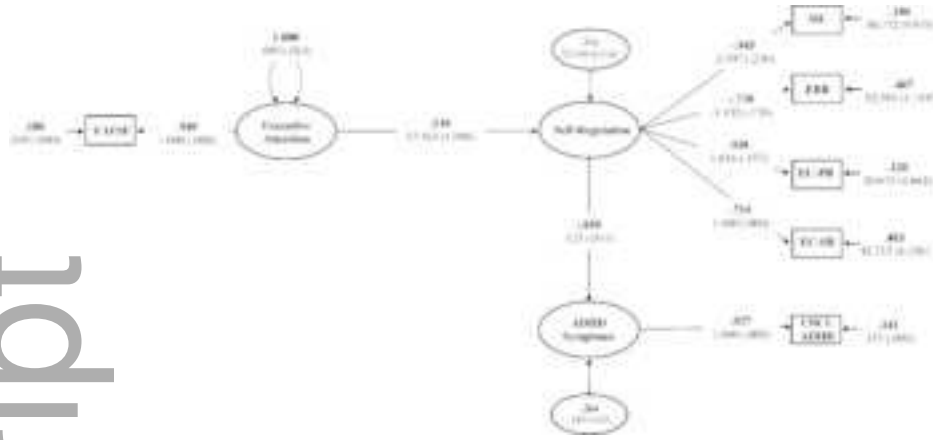
desc_12918_f5.tiff



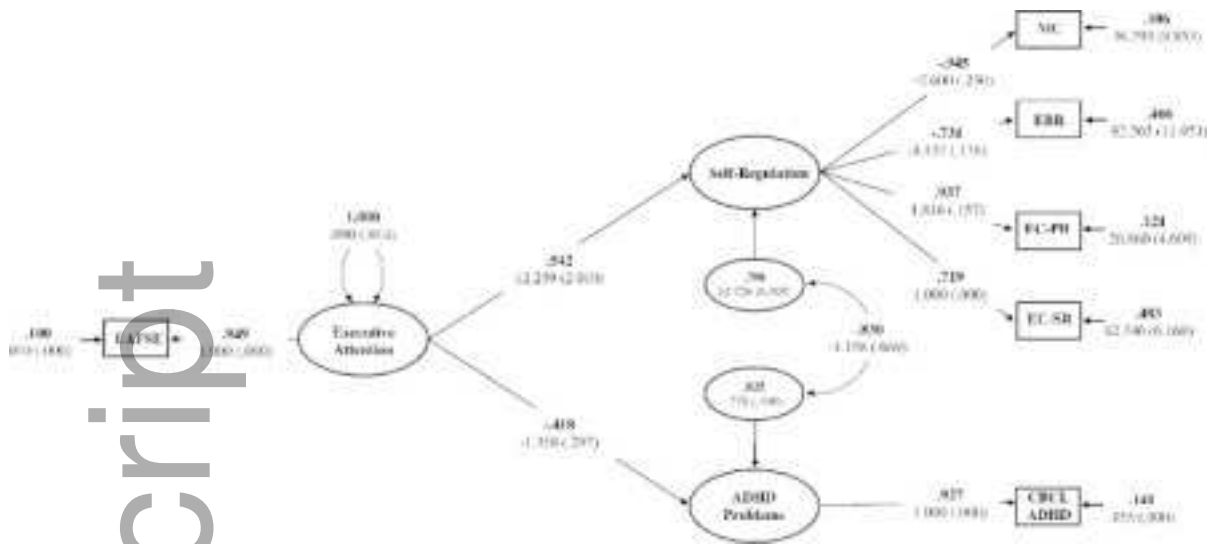
desc_12918_f6.tiff



desc_12918_f7.tiff



desc_12918_f8.tiff



desc_12918_f9.tiff