Title

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The Unity and Diversity of Executive Functions: A Systematic Review and Re-Analysis of

Latent Variable Studies

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Abstract

Confirmatory factor analysis (CFA) has been frequently applied to executive function measurement since first used to identify a three-factor model of inhibition, updating, and shifting; however, subsequent CFAs have supported inconsistent models across the lifespan, ranging from unidimensional to nested-factor models (i.e., bifactor without inhibition). This systematic review summarized CFAs on performance-based tests of executive functions and re-analyzed summary data to identify best-fitting models. Eligible CFAs involved 46 samples (N=9,756). The most frequently accepted models varied by age (i.e., preschool=one/two-factor; school-age=three-factor; adolescent/adult=three/nested-factor; older adult=two/three-factor), and most often included updating/working memory, inhibition, and shifting factors. A bootstrap re-analysis simulated 5,000 samples from 21 correlation matrices (11 child/adolescent; 10 adult) from studies including the three most common factors, fitting seven competing models. Model results were summarized as the mean percent accepted (i.e., average rate at which models converged and met fit thresholds: CFI$\geq$.90/RMSEA$\leq$.08) and mean percent selected (i.e., average rate at which a model showed superior fit to other models: ΔCFI$\geq$.005/.010/ΔRMSEA$\leq$-.010/-.015). No model consistently converged and met fit criteria in all samples. Among adult samples, the nested-factor was accepted (41-42%) and selected (8-30%) most often. Among child/adolescent samples, the unidimensional model was accepted (32-36%) and selected (21-53%) most often, with some support for two-factor models without a differentiated shifting factor. Results show some evidence for greater unidimensionality of executive function among child/adolescent samples and both unity and diversity among adult samples. However, low rates of model acceptance/selection suggest possible bias towards the publication of well-fitting, but potentially non-replicable models with underpowered samples.

Keywords: executive function; cognitive control; confirmatory factor analysis; latent variable analysis; systematic review

Public Significance Statement

Previous research has explored whether executive functions are best described as a single self-regulatory ability (i.e., unity) or a diverse set of abilities related to control over thoughts and behaviors (i.e., diversity). This systematic review identified three abilities most frequently evaluated in psychological research (i.e., inhibition, shifting, and updating/working memory), and a re-analysis of previous studies identified greater unity of executive functions during childhood and greater diversity arising from adolescence into adulthood.

The Unity and Diversity of Executive Functions: A Systematic Review and Re-Analysis of

Latent Variable Studies

In the past decade, executive functions have garnered a significant amount of clinical and

research attention in regard to their definition and measurement (Barkley, 2012; Chan, Shum,

Toulopoulou, & Chen, 2008; Jurado & Rosselli, 2007; Pickens, Ostwald, Murphy-Pace, &

Bergstrom, 2010). There has also been considerable interest in their predictive validity for

clinical and functional outcomes (e.g., childhood problem behaviors; Espy et al., 2011;

instrumental activities of daily living; Bell-McGinty, Podell, Franzen, Baird, & Williams, 2002;

Cahn-Weiner, Boyle, & Malloy, 2002). Throughout the history of neuropsychology, executive

functions have received diverse definitions. Before the term 'executive functions' debuted in the

neuropsychological literature (Lezak, 1982), researchers had linked the term 'executive' with

both frontal lobe functioning (Pribram, 1973) and control over lower-level cognitive abilities

(Baddeley & Hitch, 1974). However, despite a large body of research on executive functions, the

field lacks both a universal definition and an agreed upon form of measurement (Barkley, 2012;

Baggetta & Alexander, 2016).

Early models of executive functions detailed a 'central executive' that managed lower-

level cognitive processes in the context of working memory (Baddeley & Hitch, 1974), while

other researchers extended this concept to a system of conscious control over attention (i.e., the

Supervisory Attentional System [SAS]; Norman & Shallice, 1986). Based on clinical

conceptualizations of frontal processes (Luria, 1966), the functions of the SAS were also

attributed to the frontal lobes. These early researchers painted a relatively unitary picture of

frontal functioning and executive functions – although they did not yet use this term – where a

localized neural substrate underlies a single control function. However, successive definitions of

executive functions have illustrated the diversity of abilities falling under this umbrella term (Barkley, 2012; Baggetta & Alexander, 2016); and, further, an established body of neuropsychological research has implicated multiple brain regions that interact with the frontal lobes (e.g., parietal lobes, cerebellum) in the expression of executive functions (Alvarez & Emory, 2006; Collette, Hogge, Salmon, & Van der Linden, 2006; Keren-Happuch, Chen, Ho, & Desmond, 2014).

Prior to unitary models of higher-order cognition, clinicians commonly evaluated many of the abilities now considered executive functions (e.g., planning, self-regulation, fluency) long before scholars clustered these abilities into a common construct (Lezak, 1976). The debate between the unity and diversity of frontal functioning (Teuber, 1972) and executive functions (Miyake et al., 2000) has continued for decades, although early definitions for executive functions (e.g., Lezak, 1983; Welsh & Pennington, 1988), and nearly all definitions that followed (Barkley, 2012; Baggetta & Alexander, 2016; Jurado & Rosselli, 2007), have described the construct as multidimensional. The earliest definition of executive functions described the construct as having "four components" (Lezak, 1983, p. 507), with later descriptions defining executive functions as an "umbrella term" (Chan et al., 2008, p. 201) for a family of "poorly defined" (Burgess, 2004, p. 79), "meta-cognitive" (Oosterlaan, Scheres, & Sergeant, 2005, p. 69), or "cognitive control" (Friedman et al., 2007, p. 893) processes "used in self-regulation" (Barkley, 2001, p. 5).

Roughly 20 years ago, researchers had already proposed some 33 definitions for executive functions (Eslinger, 1996). The labels and tests for executive functions have been so diverse within the published research that one recent literature review identified 68 sub-components of executive function, reduced to 18 sub-components following an analysis that

removed semantic and psychometric overlap between terms (Packwood, Hodgetts, & Tremblay, 2011). The authors of this review reported that the large number of executive functions posited by various researchers lacked parsimony. In turn, despite years of research on diverse executive functions, the exact number of constructs rightfully labeled executive functions remains largely unknown.

Understanding the number of executive functions supported by the neuropsychological literature first requires an understanding of their measurement. The traditional measurement of executive functions in both research and clinical practice has relied largely on the use of single tests (Baggetta & Alexander, 2016; Chan et al., 2008; Rabin, Barr, & Burton, 2005; Rabin, Paolillo, & Barr, 2016). Tests purported to measure executive functions have varied significantly across studies, with task characteristics sometimes having a greater effect on test performances than the personal and diagnostic features of participants (e.g., age, gender, nature of reading difficulties; Booth, Boyle, & Kelly, 2010). With the heterogeneity of available tests of executive functions, researchers likely inferred that the many tests used to measure executive functions did not all necessarily measure the same unitary construct; however, this inference has resulted in the over-naming of task-specific behaviors as separable executive sub-components (Packwood et al., 2011). This approach ignores the high interrelatedness between both neuropsychological tests and the terms used to describe their outcomes.

Latent Variable Research on Executive Functions

A rich history of published research has explored the correlations between tests of executive functions using a factor analytic approach (Royall et al., 2002). The first factor analyses on executive functions used an exploratory approach that did not impose any hypothesized correlational structure on the battery of tests. The first appearance of an executive

function measure in a factor analysis observed the Stroop test loading on a factor involved in the cognitive control over attention (Barroso, 1983). Sequential studies found a heterogeneous number of factors, ranging from a minimum of one factor (e.g., Deckel & Hesselbrock, 1996; Della Sala, Gray, Spinnler, & Trivelli, 1998) to as many as six factors (Testa, Bennett, & Ponsford, 2012). In multiple contexts, the outcomes of many tasks measuring executive functions loaded together on task-specific factors rather than loading onto common factors composed of indicators from multiple tests (e.g., Cirino, Chapieski, & Massman, 2000; Grodzinsky & Diamond, 1992; Levin et al., 1996; Latzman & Markon, 2010). These findings suggest that the indicators included in these exploratory analyses correlated based on common method variance rather than underlying executive constructs (Barkley, 2012). These task-specific factors may derive largely from the statistical limitations of an exploratory approach, where the relationships between tasks lack a hypothesized structure and potentially group together due to non-executive abilities that also contribute to task performance (Hughes & Graham, 2002).

Many of the tasks employed to measure executive functions have an underlying multidimensional structure (e.g., the Wisconsin Card Sorting Test, Greve et al., 2005; the Trail Making Test, Sanchez-Cubillo et al., 2009), with many different cognitive abilities interacting to explain a given performance (Duggan & Garcia-Barrera, 2015). Executive function tests have a reputation for task impurity, whereby many non-executive abilities explain performances on tests purported to measure executive functions (Burgess, 1997; Miyake & Friedman, 2012; Phillips, 1997). To account for task impurity, a seminal article in the research on executive functions (i.e., Miyake et al., 2000) used a confirmatory factor analysis to assess the relationship between interrelated manifest variables commonly used in cognitive research as measures of three executive functions: the "shifting of mental sets, monitoring and updating of working memory

representations, and inhibition of prepotent responses" (p. 50). These researchers constructed a battery of diverse tasks that tapped into three established executive functions, selected based on a rich history of research. They assigned these tasks to hypothesized factors based on their common construct variance and found that a three-factor model best fit the data. In turn, they demonstrated the promise of confirmatory factor analysis at providing purer estimates of executive functions, not contaminated by non-executive method variance. Following this approach, updating, inhibition, and shifting have all received further support through a series of subsequent empirical studies reporting similar three-factor solutions from confirmatory factor models of cognitive tasks (e.g., Friedman et al., 2006, 2008; Lehto, Juujärvi, Kooistra, & Pulkkinen, 2003; Vaughan & Giovanello, 2010).

The published research on measurement models for executive functions has burgeoned in the new millennium (Willoughby, Holochwost, Blanton, & Blair, 2014). The solutions from confirmatory factor analyses accepted by past researchers have varied significantly in terms of the number of factors identified, ranging from a single factor during the preschool and school years (e.g., Brydges, Reid, Fox, & Anderson, 2012; Hughes, Ensor, Wilson, & Graham, 2010; Wiebe, Espy, & Charak, 2008) and older adulthood (e.g., de Frias, Dixon, & Strauss, 2006; Ettenhofer, Hambrick, & Abeles, 2006) to as many as five during young adulthood (i.e., Fournier-Vicente, Larigauderie, & Gaonac'h, 2008). Research on the latent structure of executive function spans all stages of life, but a substantial focus of this research has surrounded the early development of higher-order cognitive abilities (Garon, Bryson, & Smith, 2008; Müller & Kerns, 2015), and a smaller amount of previous work has discussed their development beyond the foundational years of life and into adolescence (Best & Miller, 2010; Best, Miller, & Jones, 2009). Much attention has been given to the differentiation of executive functions over the

course of development (Bardikoff & Sabbagh, 2017), often using a latent variable approach to examine whether factor models support unitary or multidimensional solutions at different ages (e.g., Brydges, Fox, Reid, & Anderson, 2014). Many one-factor solutions have arisen from studies on early executive function development (e.g. Wiebe et al., 2008, 2011; Willoughby, Blair, Wirth, Greenberg, & The Family Life Project Investigators, 2012a), but researchers have criticized the methodology used among young children, where some executive function constructs are rarely evaluated (e.g., shifting) and interpreted as absent, even though they have not been empirically measured by the researchers (Bardikoff & Sabbagh, 2017). Nonetheless, there is evidence for a gradual differentiation of executive function abilities, beginning even prior to the preschool years (Best & Miller, 2010; Garon et al., 2008), where executive functions theoretically transition from a single function to a set of diverse, interactive processes, as many studies on school-aged children, adolescents, and adults found multidimensional solutions of correlated factors (Friedman, Miyake, Robinson, & Hewitt, 2011; Miyake et al., 2000; Letho et al. 2003).

In terms of cognitive development, the idea of differentiation is not specific to executive functions (Garrett, 1946; Werner, 1957); however, considering the rich empirical research on executive functions in early life, it has gained ground in explaining the changes that occur in the structure of executive functions over the course of development. Some recent interpretations of the executive function literature (Bardikoff & Sabbagh, 2017; Müller & Kerns, 2015) have recruited the interactive specialization framework to explain this differentiation, where cortical areas are functionally non-specific early in life, but over the course of development, become increasingly specialized through activation, interactions, and experience (Johnson, 2000, 2011). Development and organization of basic structural and functional neural networks from birth

onwards support greater systems-level integration later in development, particularly within

networks that are specialized in executive processing (Luna, Marek, Larsen, Tervo-Clemmens, &

Chahal, 2015). Several reviews on the development of executive functions have focused

specifically on the neurodevelopment of the three constructs included in the first measurement

model reported for executive functions (i.e., inhibition, updating, and shifting; Miyake et al.,

2000); however, the factors included in this model do not necessarily represent an exhaustive list

of empirically supported executive functions (Jurado & Rosselli, 2007) and, notably, Miyake and

colleagues (2000) never described them as such. The terms most commonly used to label

executive functions include planning, working memory, fluency, inhibition, and set-shifting

(Packwood et al., 2011); however, these terms simply present most frequently in the literature.

The discussion of how many executive functions exist implies that the many abilities

labeled "executive" represent separable cognitive capacities; however, each factor does not

necessarily represent an orthogonal construct, considering the medium to large correlations often

observed between the latent variables of different functions (e.g., .63 to .65, Lehto et al., 2003;

.42 to .63, Miyake et al., 2000; .68 to .81, Vaughan & Giovanello, 2010). Working memory

capacity and vocabulary both significantly predict outcomes on fluency tasks (Unsworth,

Spillers, & Brewer, 2011) and fluency may represent a confluence of working memory

interacting with the lexicon (Shao, Janse, Visser, & Meyer, 2014). Similarly, planning represents

a higher-order construct, with updating, shifting, and inhibition potentially operating in a

collaborative fashion to explain performances on planning-related tasks (Miyake & Friedman,

2012). The exact relationship between updating, shifting, and inhibition is still not defined, and

more recent studies have found that the majority of variance in these three executive functions

may be explained by a common higher-order dimension (e.g., Fleming, Heintzelman, &

Bartholow, 2016; Friedman et al., 2008; Ito et al., 2015).

Considering the conceptual and empirical overlap between updating, shifting, and

inhibition, researchers have begun re-evaluating the shared variance between the constructs

through an alternative measurement model (e.g., Friedman et al., 2008, 2011, 2016; Friedman,

Corley, Hewitt, & Wright, 2009). Using a nested factor model in repeated analyses of the same

dataset, Friedman and colleagues (2008, 2009, 2011, 2016) had all indicators load on a general

factor and indicators for updating and shifting co-load on factors specific to those constructs.

Because the general factor fully explained the variance in inhibition, the researchers did not

include it as a specific factor, with its indicators loading only on the general factor. This model

represents an incomplete bifactor model (Chen, West, & Sousa, 2006) and demonstrates a

substantial amount of shared variance between indicators across factors in a multidimensional

test battery. These findings emphasize the need to consider both general and specific dimensions

when explaining performances on test batteries evaluating executive functions.

Aims of the Systematic Review and Re-Analysis

Considering the recent conclusions of Miyake and Friedman (2012) and the many

published confirmatory factor analyses supporting multidimensional solutions using

performance-based tests (Willoughby et al., 2014), the latent variable research on executive

functions has reached a point of requiring both knowledge synthesis and a re-evaluation of

previously supported factor solutions. Foremost, the published literature on executive function

measurement models has never been comprehensively summarized, and a systematic review

would identify the factor models with the most empirical support. Further, few researchers aside

from Friedman and colleagues (2008, 2009, 2011, 2016) have evaluated the presence of a

common executive function dimension through the nested factor modeling approach described earlier (e.g., Fleming et al., 2016; Garza et al., 2014; Ito et al., 2015; Kramer et al., 2014), but all of these researchers have found a robust general factor. In turn, those researchers not exploring a general dimension potentially over-estimate the diversity of executive function factors. A re-analysis of previous findings would provide a basis to evaluate whether a nested factor model offers superior statistical fit to a multidimensional solution.

The term executive function has become increasingly common within academic literature over the last decade (Willoughby et al., 2014), along with extensive citations of latent variable research (e.g., Miyake et al., 2000) to rationalize the measurement of specific constructs in various research designs. Considering the increased scholarly focus on executive functions, a close assessment of which factor models and constructs have the most empirical evidence will guide researchers when developing their own studies, ensuring their measures target constructs supported by previous scientific inquiry. As well, considering the inferences that have been drawn about the differentiation of executive functions over the lifespan (Bardikoff & Sabbagh, 2017; Jurado & Rosselli, 2007; Müller & Kerns, 2015), a summary of latent variable research will further elucidate the developmental sequence through which executive functions arise. Lastly, the identification of evidence-based factor models can inform the hypothesized structure of new test batteries to measure executive functions for implementation into either research or clinical practice.

The current study aimed to (a) determine the empirical support for measurement models of executive functions proposed by past researchers, (b) identify the number of purported executive functions supported by confirmatory factor analyses in the current literature, and (c) determine which published measurement model best fits summary data across studies. To fulfill

the first two aims, the current study involved a broad systematic review of research reporting

confirmatory factor analyses on batteries of performance-based tasks evaluating executive

functions, summarizing both the frequency of model solutions (e.g., unidimensional, three-factor,

nested factor models) and the rate at which different factors were included in accepted

measurement models (e.g., inhibition, updating, shifting). Considering the significant

heterogeneity between the measurement models evaluated by past researchers, the approach to

the third aim required a narrower focus on comparable studies, and ultimately considered only

those studies assessing the most frequently evaluated factor model within the published

literature: the three-factor measurement model of inhibition, shifting, and updating/working

memory (Miyake et al., 2000), with updating and working memory merged into

updating/working memory because these terms are often used interchangeably in latent variable

research. The results of these comparable studies were re-analyzed and fitted to competing factor

solutions based on the published literature. The approach of this review was guided by data

rather than theory, summarizing past research findings rather than proposing a new model of

executive functions. By fulfilling these aims, the current review described the diversity of

existing latent variable research on executive functions and further clarified the strength of

empirical evidence behind the most common factor solutions proposed by past researchers.

Method

The report of this systematic review followed the Preferred Reporting Items for

Systematic Reviews and Meta-Analyses (PRISMA) Statement (Moher, Liberati, Tetzlaff,

Altman, and the PRISMA Group, 2009). This review involved only the qualitative and

quantitative re-analysis of summary data from published studies, and such a review is exempt

from our internal ethics review process. Prior to the literature search, inclusion criteria were

established to identify appropriate articles. For inclusion, articles needed to (a) involve a sample

or sub-sample of cognitively healthy participants (i.e., without a neurodevelopmental or

neurological disorder known to significantly impact cognitive performance) and (b) report a

confirmatory factor analysis of a multidimensional measurement model of executive function.

Following this criterion, studies that included multiple factors that could be conceptualized as

executive functions, but not directly specified by the authors as dimensions of executive function

or a synonymous construct (e.g., executive control) were ineligible. As well, measurement

models of solely sub-components of executive function were ineligible (e.g., inhibition, Aichert

et al., 2012, Friedman & Miyake, 2004; effortful control, Allan & Lonigan, 2011, 2014; problem

solving; Cinan, Özen, & Hampshire, 2013; Scherer & Tiemann, 2014). Eligible models needed

to include (c) a minimum of two indicators, deriving from separate tests, per construct evaluated

and (d) only performance-based cognitive or neuropsychological outcomes as indicators for the

executive function factor(s) (i.e., studies including biometrics, rating scales or symptom

inventories as indicators were deemed ineligible for this review), deriving from (e) at least three

separate cognitive or neuropsychological tests (i.e., measurement models evaluating the factor

structure of multiple outcomes from a single neuropsychological test were ineligible). Lastly, the

articles needed to (f) be published in either a peer-reviewed journal or academic book and (g) be

written in the English language. For inclusion in the re-analysis, which synthesized a comparable

sub-sample of studies testing the most commonly evaluated measurement model in the literature,

the articles needed to meet all aforementioned criteria, but also had to have (h) evaluated a

measurement model including factors of inhibition, shifting, and updating (or analogous

constructs; e.g., mental set-shifting, switching, working memory, etc.) and (i) provide sufficient

summary data for re-analysis (i.e., at least a correlation matrix for all test items included in the model).

Literature Search

The systematic literature search covered dates between January 1998 and November 2016. The lower bound of this data range was designated to capture articles following the publication of Miyake et al. (2000) and any articles published just prior to this study that may have involved a confirmatory factor analysis of tests of executive functions. The electronic search strategy involved online searches of the following databases, with search restrictions in parentheses: PsycInfo (Publication type – Peer-reviewed journals, All books; Methodology – Empirical studies, Quantitative studies; Population group – Human; Language – English), PsycArticles (Publication type – Empirical studies, Quantitative studies; Population group – Human), MedLine (Publication type – Journal article; Population group – Human; Language – English), and CINAHL (Publication type – Journal article, Book, Book chapter, Research, Statistics; Language – English). The search protocol involved the following Medical Subject Headings (MeSH), Psychological Index Terms (Tuleya, 2009), and search terms:

((MM "Factor Analysis" OR MM "Factor Structure" OR MM "Goodness of Fit" OR MM "Structural Equation Modeling") OR (MM "Factor Analysis, Statistical" OR MM "Models, Statistical") OR ("confirmatory factor analysis" OR "CFA" OR "latent variable")) AND ((DE "Executive Function" OR DE "Cognitive Control" OR DE "Set Shifting" OR DE "Task Switching" OR MM "self regulation") OR (MM "Executive Function" OR MM "Inhibition (Psychology)" OR MM "Problem Solving") OR ("executive function*" OR "self-regulat*"))

All retrieved search results were screened twice to ensure that no study went overlooked (Edwards et al., 2002). Following the electronic search, reference lists from peer-reviewed journals were manually searched over the course of data extraction and manuscript preparation, identifying any articles missed by the electronic search protocol (See Figure 1, for a flow diagram of the systematic review process along with the number of articles identified).

[INSERT FIGURE 1 ABOUT HERE]

Data Extraction

Two independent reviewers extracted relevant information from each article through use of a common data collection spreadsheet. Both reviewers extracted variables related to study characteristics (i.e., authorship, year of publication), sample characteristics (i.e., percent female, mean age, mean years of education, ethnic composition), model characteristics (i.e., name of dependent variables and respective factors), and factor analytic results for accepted measurement models (i.e., χ^2 value and respective *p*-value; comparative fit index, CFI; root mean squared error of approximation, RMSEA). For samples eligible for the re-analysis, summary data necessary for a re-analysis of the measurement model was also extracted (i.e., sample size, means/standard deviations, correlation/covariance matrix).

To quantify study quality, reviewers rated articles based on a scale developed specifically for the current review. The majority of confirmatory factor analytic studies involve observational research designs with one time point of data collection (Willoughby et al., 2014), which represents one of the lowest levels of scientific evidence (OCEBM Levels of Evidence Working Group, 2011). Few instruments for rating the quality of this level of research exist in the literature (Sanderson, Tatt, & Higgins, 2007; Vandenbroucke et al., 2007). In turn, the current systematic review strategy applied eleven criteria to rate study quality. These criteria were based

largely on standard publication practices for factor analyses (Schreiber, Nora, Stage, Barlow, & King, 2006), with each item scored as either met (1 point) or not met (0 points) and summed for a total study quality score (range: 0-11). The study quality rating scale included the following items:

(1) the researchers reported a sample size with $\hat{\pi} \geq .80$ to reject the null hypothesis (RMSEA $\geq .05$) for a model obtaining a perfect RMSEA (Hancock, 2006), (2) listed at least two demographic variables for each sample evaluated (e.g., mean age, gender composition), (3) indicated that data screening/cleaning for outliers or data transformations to ensure normality was conducted, (4) provided a path diagram of at least one measurement model evaluated or a structural model including all variables from the accepted measurement model, (5) reported the results of a χ^2 goodness-of-fit test and at least two alternative fit indices (e.g., RMSEA, CFI, etc.), (6) listed all of the loadings and (7) residuals for at least one measurement model or structural model evaluated, (8) provided inter-factor correlations (or covariances) for at least one of the multidimensional measurement models or structural models evaluated (if constrained to zero, the authors reported this constraint in the manuscript), (9) reported the means and standard deviations for all manifest variables included in the measurement model, (10) provided a correlation or covariance matrix including all manifest variables included in the measurement model, and (11) had at least three indicators loading on each latent factor in every measurement model evaluated (Roberts & Grover, 2009).

The selection of the power criterion in this scale was based on post-hoc power analyses for model fit that were calculated based of previously published criteria. A power ($\hat{\pi}$) cutoff of $\geq .80$ was selected as a conventional threshold in power analysis (Cohen, 1992). Hancock (2006)

provides tables to calculate post-hoc power to reject the null hypothesis (i.e., RMSEA ≥ .05) based on three RMSEA values (.00, .02, .04). The tables for the perfect RMSEA value (i.e., .00) were used to determine whether models met sufficient power (i.e., $\hat{\pi} \geq .80$) because (a) many studies reported perfect RMSEA values and (b) these tables list the smallest required sample sizes to meet this threshold. Stricter thresholds would have resulted in few or no studies meeting this criterion.

Re-Analysis

All articles eligible for the re-analysis provided a correlation matrix for their test battery (included in the Supplementary Materials) and tested the same three-factor model, including factors of inhibition, updating, and shifting or analogous constructs. One study included in the re-analysis (Hedden & Yoon, 2006) reported two factors that could be considered inhibition-related factors (i.e., prepotent response inhibition and resistance to proactive interference). Because prepotent response inhibition was most analogous to the inhibition factor included in other measurement models also eligible for the re-analysis, this factor was included as the inhibition factor in all models run using the correlation matrix for this study, while the resistance to proactive interference factor was left out.

The re-analysis involved two primary aims that rationalized the methodological approach. First, not all researchers examined all factor models supported by the literature with their dataset, and a re-analysis specifying multiple possible measurement models would determine if a specific factor model tended to fit best across published samples. Second, the risk for publication bias was of concern, because most publications identified in the systematic review reported small samples and excellent-fitting models that converged without any errors.

The correlation matrix was re-analyzed by specifying seven alternative measurement models: a unidimensional model, three two-factor models that merged two of the first-order factors (i.e., inhibition = updating; updating = shifting; inhibition = shifting), a three-factor model (i.e., inhibition, updating, and shifting), a nested factor model (i.e., a common executive function bifactor, with shifting-specific and updating-specific factors co-loading on their select indicators and no inhibition-specific factor), and a bifactor model (i.e., a common executive function bifactor with specific factors for inhibition, shifting, and updating). See Figure 2 for a visual representation of each model. Six of these seven models (i.e., all but the bifactor model) were identified as published factor solutions by at least one study in the systematic review. While the full bifactor model was not accepted by any researchers, it was tested as a comparison point for the nested factor model (as done originally by Friedman et al., 2008), permitting evaluation of whether the removal of the inhibition-specific factor improved the fit of the model.

The re-analysis was conducted through a parametric bootstrap simulation based on the published correlation matrix where the data from each study were assumed to be multivariate normal with the observed correlation matrix considered equivalent to the population correlation matrix. For each sample, correlation matrices were computed for 5,000 simulated datasets of equal sample size to that of the original study. For all 5,000 correlation matrices, each factor model was fit to the data. Fit indices were calculated for models that "properly converged," which means the model converged without any errors that would indicate a solution was inadmissible or the estimates were not trustworthy (e.g., a correlation larger than absolute 1.0, negative residual variances, a non-positive definite latent variable covariance matrix). Throughout the rest of this manuscript, the terms properly converged and converged will be used synonymously. For all samples that properly converged, the CFI and RMSEA were calculated.

All factor variances were fixed to 1.0 to set the metric for the factor, and all loadings were freely

estimated for all models, with one exception: models with only two indicators on any specific

factor in the bifactor or nested factor models had the loadings for those indicators set to be equal

for purposes of model identification, as done by previous researchers (Canivez, 2014; Watkins,

2010). The bootstrap re-analysis was conducted in R (R Core Team, 2013), with all factor

models fit using the Lavaan package (Rosseel, 2012). The bootstrapping method was validated

by testing the accepted models for the Wechsler Adult Intelligence Scale, Fourth Edition (WAIS-

IV; Wechsler, 2008) and the Wechsler Intelligence Scale for Children, Fifth Edition (WISC-V;

Wechsler, 2014) using published correlation matrices available in the technical manuals for these

tests. More details on this validation, along with the results, are provided in the Supplementary

Materials.

[INSERT FIGURE 2 ABOUT HERE]

Model Fit Interpretation. Model fit was evaluated by use of the CFI and RMSEA.

These fit indices were selected for three reasons. First, they are commonly reported in the

executive function literature, which is why they were included as extracted data elements for the

systematic review. The majority of eligible studies reported these fit indices, and researchers

within this field are familiar with their use. Second, they are not sensitive to sample size (Fan,

Thompson, & Wang, 1999), which was important because the sample sizes varied substantially

between studies. And third, they provide a common metric that is comparable across models and

offer standard thresholds for acceptable fit and cutoff criteria when comparing alternative

models. The RMSEA was also a good choice because it favors parsimony (Hooper, Coughlan, &

Mullen, 2008), which was meaningful when comparing models that ranged from simple

unidimensional models to those with far more estimated parameters, such as the bifactor model.

Lenient and strict thresholds for acceptable fit and cutoffs for model comparisons in fit were used to guide model acceptance and selection for both the CFI and RMSEA. For the CFI, the lenient and strict thresholds for acceptable fit were ≥ .90 (Bentler & Bonett, 1980) and ≥ .95 (Hu & Bentler, 1999), respectively; and for the RMSEA, the lenient and strict thresholds were ≤.08 and ≤.05, respectively (Browne & Cudeck, 1993). Both the CFI and RMSEA also have cutoffs for significant improvements in model fit when comparing competing models. The lenient and strict cutoffs for change in CFI (i.e., ΔCFI) were ≥.005 and ≥.010, respectively, while the lenient and strict cutoffs for change in RMSEA (i.e., ΔRMSEA) were ≤-.010 and ≤-.015, respectively (Chen, 2007).

The simulated data were interpreted in two ways. The first interpretation evaluated the rate of model acceptance, meaning the percent of bootstrapped models that both converged and met lenient and strict cutoffs for the CFI and RMSEA. Across studies, the means and medians of percent convergence, percent meeting fit thresholds, and percent both converging and meeting fit thresholds (i.e., the rate of model acceptance) were calculated. These percentages were taken to identify the frequency at which a researcher with data from a battery of executive function tests would (a) have their proposed model converge without any errors that would affect inference and (b) meet standard fit criteria.

The second interpretation evaluated the comparable preference for each model through direct comparisons in fit between competing models. The models were arranged hierarchically based on parsimony for model comparisons, from highest to lowest model complexity: bifactor, nested factor, three-factor, two-factor models (i.e., three different models, all equally parsimonious), and one-factor. For each bootstrapped sample, each model was directly compared to all other models evaluated based on lenient and strict cutoffs for ΔCFI and ΔRMSEA. If a

model presented significantly better fit based on a cutoff, it was preferentially selected over an alternative model. If the differences in ΔCFI or ΔRMSEA did not exceed the cutoff, then the more parsimonious model was preferentially selected. If the models were equivalently parsimonious (i.e., the two-factor models), whichever model had the best fit based on absolute CFI or RMSEA was preferentially selected. The results of these analyses were interpreted based on (a) the percent of bootstrapped samples where the model properly converged and was selected based on the ΔCFI or ΔRMSEA cutoffs (hereafter referred to as percent model selection), and (b) the percent of bootstrapped samples where the model was selected based on the ΔCFI or ΔRMSEA cutoffs among only those samples where the model properly converged (hereafter referred to as percent contingent model selection). Across studies, the means and medians of the percent model selection and percent contingent model selection were taken.

The percent model selection summarizes the frequency at which a researcher with data from a battery of executive function tests would have a model converge and select that model over competing models. The percent contingent model selection summarizes the frequency at which a researcher would select a model among only those samples where that model properly converged (i.e., in samples where that model converges, how often it has superior fit to competing models). The comparison between models was made regardless of whether or not the models met standard fit thresholds. In turn, even if a model is selected over other models with a high frequency, the model does not necessarily meet the conventional fit thresholds used to interpret rates of model acceptance (i.e., CFI ≥ .90/.95; RMSEA ≤ .05/.08). In turn, the percent model acceptance and model selection must be interpreted in combination.

Results

Systematic Review

The literature review identified 40 articles meeting eligibility criteria for the systematic review reporting measurement models for 46 different samples (see Figure 1). Among those eligible studies, 17 articles provided sufficient data for the re-analysis of 21 samples. A reference list of full-text articles reviewed during the literature search, but ultimately not included in the systematic review, is provided in the Supplementary Materials along with a reason for their exclusion.

A large set of studies examined for the current review pulled participants from the Victoria Longitudinal Study (de Frias, Dixon, & Strauss, 2006, 2009; McFall et al., 2013, 2014; Sapkota, Vergote, Westaway, Jhamandas, & Dixon, 2015; Thibeau, McFall, Wiebe, Anstey, & Dixon, 2016), the Colorado Longitudinal Twin Study (Friedman et al., 2006, 2007, 2008, 2009, 2011, 2016), and the Family Life Project study (Willoughby, Blair, & The Family Life Project Investigators, 2016; Willoughby, Blair, Wirth, Greenberg, & The Family Life Project Investigators, 2010; Willoughby et al., 2012a; Willoughby, Wirth, Blair, & The Family Life Project Investigators, 2012b) with definitive or potential overlap among the participants included in their analyses. Some cross-sectional studies also reported analyses for the same participant data across different articles (Miller, Giesbrecht, Müller, McInerney, & Kerns, 2012; Miller, Müller, Giesbrecht, Carpendale, & Kerns, 2013; van der Ven et al., 2012, 2013; Usai, Viterbori, Traverso, & De Franchis, 2014; Viterbori, Usai, Traverso, & De Franchis, 2015; Rose, Feldman, & Jankowski, 2011, 2012). To avoid representing the same participants twice in the review, the studies involving the largest samples and the most executive function tasks were ultimately

included in the systematic review and re-analysis (de Frias et al., 2009; Friedman et al., 2011;

Miller et al., 2012; Rose et al., 2012; van der Ven et al., 2013, Willoughby et al., 2012a).

Most studies reporting confirmatory factor analyses on executive functions involved

cross-sectional research designs; and for the limited amount of longitudinal studies identified,

only one wave of measurement per study was represented in the current review and re-analysis.

For one longitudinal study evaluating the same battery of executive function tasks at multiple

time points, the data from the first wave were considered for the current review and re-analysis

(i.e., de Frias et al., 2009). The consideration of just the first wave data made the study design

more comparable to other studies in the review; however, in contexts where the task battery

changed, the wave with the most available executive function tasks or the most complete

summary data was considered in the current review (i.e., Willoughby et al., 2012a; Lee et al.,

2013).

Qualitative Synthesis

Demographics of samples evaluated. Table 1 provides the demographic characteristics

for each sample included in the systematic review along with an estimate of study quality.

Among the samples reported by studies included in the systematic review, 9 samples ($n = 2{,}614$;

$\bar{x}$ % female = 49.81%) consisted of preschool aged children ($\bar{x}$ age range: 3.01 to 5.77 years), 15

samples ($n = 2{,}374$; $\bar{x}$ % female = 48.54%) consisted of school-aged children ($\bar{x}$ age range: 6.42

to 11.88 years), 3 samples ($n = 1{,}040$; $\bar{x}$ % female = 48.87%) consisted of adolescents ($\bar{x}$ age

range: 14.41 to 17.30 years), 9 samples ($n = 2{,}070$; $\bar{x}$ % female = 51.27%) consisted of adults ($\bar{x}$

age range: 19.75 to 25.70 years), and 8 samples ($n = 1{,}112$; $\bar{x}$ % female = 61.44%) consisted of

older adults ($\bar{x}$ age range: 60.24 to 74.40 years). Two studies evaluated samples with participants

spanning multiple age groups ($n = 546$), including a child to young adult sample ($\bar{x}$ age range:

7.20 to 20.80 years; Huizinga et al., 2006) and a merged young and older adult sample ($\bar{x}$ age

range: 21.00 to 71.00 years; Pettigrew & Martin, 2014). Overall, 9,756 participants ($\bar{x}$ % female

= 52.56%) were represented in the systematic review.

Among the 18 samples with some race or ethnicity information provided, 10 samples

were predominantly White, 3 samples were majority non-White, and 5 samples were identified

as ethnically Chinese (Lee et al., 2012; Xu et al., 2013) or from Chinese schools (Duan et al.,

2010). Study quality was on average 8.32 (SD = 1.91; range: 1 to 11) across age groups. It was

similar on average for preschool children ($\bar{x}$ = 8.56), school-aged children ($\bar{x}$ = 8.31), adolescents

($\bar{x}$ = 8.00), and adults ($\bar{x}$ = 9.22). It was lower for older adults ($\bar{x}$ = 6.86) due to one study

receiving a single study quality point (Frazier et al., 2015). When this outlier was removed, the

mean study quality for older adult studies increased to 7.83, which was more similar to the other

age bands.

[INSERT TABLE 1 ABOUT HERE]

Model fit indices and accepted models. Table 2 provides fit indices for accepted

measurement models identified by the systematic review, along with estimated power (based on

N and *df*; Hancock, 2006), the number of factors, and names of factors included in the accepted

model. Considering fit indices, all accepted models had CFI values ≥ .95 and all RMSEA values

≤ .06 (with the exception of one study with CFI = .92; McVay & Kane, 2012), indicating

excellent statistical fit for the models (Hu & Bentler, 1999). These excellent model fit statistics

stood in contrast to the predominantly low power estimates across studies, which came to an

average of 0.44 (SD = 0.32; range = 0.08 to 0.99). The accepted models included anywhere

between one to five factors. Overall, 8 studies accepted a one-factor model (17.39%), 18

accepted a two-factor model (39.13%), 14 accepted a three-factor model (30.43%), 1 accepted a

four-factor model (2.17%), 1 accepted a five-factor model (2.17%), and 4 accepted a nested

factor model (8.70%). For the calculation of these totals and those reported below, Carlson et al.

(2014) was considered to have accepted a one-factor model based on parsimony, although these

authors specified no preference between a one-factor or two-factor model; and de Frias et al.

(2009) accepted a two-factor model for their Cognitively Normal Subsample, although this

model was never formally evaluated.

For preschool samples, roughly half of researchers accepted a one-factor model solution

(Number of studies [*k*] = 5; 55.56%; Carlson et al., 2014; Masten et al., 2012; Wiebe et al., 2008,

2012; Willoughby et al., 2012a), while the other half preferred a two-factor solution (*k* = 4;

44.44%; Lerner & Lonigan, 2014; Miller et al., 2012; Monette et al., 2015; Usai et al., 2014).

Among the school-aged samples, the most commonly accepted model was the three-factor model

(*k* = 7; 46.67%; Agostino et al., 2010; Arán-Filippetti, 2013, Duan et al., 2010; Lambek &

Shevlin, 2011; Lehto et al., 2003; Rose et al., 2012), while a smaller set of studies supported a

two-factor (*k* = 4; 26.67%; Brocki & Tillman, 2014; Lee et al., 2012, 2013; van der Ven et al.,

2013) or one-factor solution (*k* = 3; 20%; Brydges et al., 2012; Xu et al., 2013). One study

involving a school-aged sample supported a model best categorized as a nested factor model (*k* =

1; 6.67%; van der Sluis et al., 2007), although these researchers did not label it as such. Among

the three adolescent studies, researchers reported a single nested factor model (*k* = 1; 33.33%;

Friedman et al., 2011) and a pair of three-factor models (*k* = 2; 66.66%; Lambek & Shevlin,

2011; Xu et al., 2013). For the adult studies, the support was roughly split between a two-factor

model (*k* = 3; 33.33%; Klauer et al., 2010; McVay & Kane, 2012; Was, 2007), a three-factor

model (*k* = 2; 22.22%; Klauer et al., 2010; Miyake et al., 2000), and a nested factor model (*k* = 2;

22.22%; Fleming et al., 2016; Ito et al., 2015). One study supported a four-factor model (*k* = 1;

11.11%; Chuderski et al., 2012) and another supported a five-factor model ($k = 1$, 11.11%; Fournier-Vicente et al., 2008). The older adult samples predominantly supported a two-factor model ($k = 5$, 62.5%; Bettcher et al., 2016; de Frias et al., 2009; Frazier et al., 2015; Hedden & Yoon, 2006; Hull et al., 2008), while a smaller, but substantial percentage supported a three-factor model ($k = 3$, 37.5%; Adrover-Roig et al., 2012; de Frias et al., 2009; Vaughan & Giovanello, 2010).

[INSERT TABLE 2 ABOUT HERE]

Table 3 provides counts and frequencies of how often a specific construct was represented in an accepted factor model. The most common factors were those included in the original measurement model by Miyake and colleagues (2000), with updating/working memory ($k = 33$; 71.74% of models) being the most frequent, followed by inhibition ($k = 24$; 52.17%), and then by shifting ($k = 20$; 43.48%). A small number of studies merged these factors, including inhibition and shifting ($k = 5$; 10.87%), inhibition and updating/working memory ($k = 1$; 2.17%), and shifting and updating/working memory ($k = 3$; 6.52%). Two studies included factors of strategic retrieval or access to long-term memory ($k = 2$; 4.35%; Adrover-Roig et al., 2012; Fournier-Vicente et al., 2008).

Some differences occurred in terms of the factors represented across age spans. A global executive function factor was represented among 23.91% of models ($k = 11$), but constituted a unidimensional factor among children and a nested bifactor among adolescents and adults. No sample beyond the school-aged years provided a unidimensional model solution, and a global executive function factor was not observed among any eligible older adult samples. No preschool sample identified shifting as a separate factor, while all three factors were represented in all groups above 6 years of age.

[INSERT TABLE 3 ABOUT HERE]

Tests used as indicators. In the Supplementary Materials, Tables S1 and S2 list the indicators organized by factors for child/adolescent and adult studies, respectively. The division between child/adolescent and adult samples was set at a mean age of 16 years, where those with a mean age at or below 16 years were considered child/adolescent ($k = 21$) and those with a mean age over 16 years were considered adult ($k = 18$). Few studies involved the same battery of tests for all indicators evaluated, but a small number of measures were common in the evaluation of specific constructs. The tests below are categorized based on either task or paradigm, and do not necessarily indicate that the studies were using the exact same task or the exact same dependent variable derived from that task. In some contexts, the exact same task or a highly similar task was used across studies (e.g., Digit Span Backward); however, in other contexts, a similar paradigm was used to guide the design of similar, but distinguishable tasks. For example, the Stroop paradigm among children comes in multiple different varieties of tasks, including a Boy-Girl Stroop, Day-Night Stroop, and Color-Word Stroop; all of which involve different stimuli, but similar task demands, and they load onto inhibition.

The most frequent indicator of inhibition for child/adolescent studies were tasks using the Stroop paradigm ($k = 11$), followed by tasks using the Go/No-go paradigm ($k = 7$). Tasks using a Tower paradigm were the third most common indicator for inhibition among child/adolescent studies ($k = 4$). The most commonly used indicator for updating/working memory was the Digit Span Backward task ($k = 7$), followed by the Letter-Number Sequencing task ($k = 3$) and tasks using the n-back paradigm ($k = 3$). For shifting, tasks with card sorting paradigms were the most commonly used as indicators ($k = 6$), while tasks using a Trail Making paradigm were the second

most commonly used ($k = 5$) and tasks using a verbal fluency paradigm were the third most

commonly used ($k = 4$).

In terms of adult studies, there was a greater frequency at which specific measures were

used as indicators across studies. For inhibition, a substantial portion of the adult studies used

tasks involving a Stroop paradigm ($k = 16$), followed by an Antisaccade task ($k = 11$), and then a

Stop-Signal task ($k = 7$). For updating/working memory, the most frequently used indicators

were tasks using the *n*-back paradigm ($k = 8$) and the Letter Memory task ($k = 8$), followed by

the Keep Track task ($k = 6$) and Digit Span Backwards task ($k = 5$). The measurement of shifting

was more variable, but still a substantial portion of researchers used the Number-Letter task ($k =$

10), followed by the Plus-Minus task ($k = 5$) and the Local Global task ($k = 4$).

The data extraction protocol involved the extraction of the task names, and did not focus

on the specific dependent variables derived from each of these tasks that were ultimately

included in measurement models. A post-hoc evaluation explored the variety of scores that

different researchers used in their models for the most commonly used paradigm: the Stroop task

as an indicator for inhibition. The Stroop task consists of congruent/neutral conditions along with

incongruent conditions. In congruent/neutral conditions, participants read color words (e.g., blue,

red) written in either black ink or their corresponding ink color, or they named the ink color of a

non-verbal stimulus (e.g., a line of asterisks or X's). In the incongruent condition, participants

see color words written in incongruent ink colors (e.g., blue written in red ink) and they are

asked to read the ink color, inhibiting the automatic response of reading the word. Among

children, similar tasks use alternative stimuli, such as the Day-Night Stroop where children are

shown a sun or moon and asked to say night or day, respectively.

Among the 11 child/adolescent studies using a Stroop-like task, 7 studies included a Stroop Color-Word paradigm, while the remainder involved Day-Night, Boy-Girl, or other Stroop-like task. Within the 7 studies using the color-word approach, 6 different dependent variables were identified, including the difference in time-to-completion between the incongruent and neutral/congruent conditions (Agostino et al., 2010; Brydges et al., 2012), the total number correct in the incongruent condition (Arán-Filippetti, 2013), the difference in the number of correct responses between the incongruent and neutral/congruent conditions (Brocki et al., 2014), the median response latency on incongruent trials (Huizinga et al., 2006), the number of items named per second (van der Sluis et al., 2007), and the reaction time difference between incongruent and neutral/congruent conditions (Xu et al., 2013).

Among the 16 studies using a Stroop paradigm among adult samples, 6 different dependent measures were derived from the same test, including a reaction time difference score between incongruent and neutral/congruent conditions (Fleming et al., 2016; Friedman et al., 2011; Fournier-Vicente et al., 2008; Hull et al., 2008; Ito et al., 2015; Klauer et al., 2010; Miyake et al., 2000; Was, 2007), a ratio of proportion correct in the incongruent condition to proportion correct in the neutral/congruent condition (Chuderski et al., 2012), an interference index (de Frias et al., 2009), the total correct in the incongruent condition statistically controlling for the total correct in the neutral/congruent condition (Bettcher et al., 2016; Frazier et al., 2015; Pettigrew et al., 2014), the reaction time for correct incongruent trials (Vaughan & Giovanello, 2010), and the reaction time for incongruent trials regardless of accuracy (McVay & Kane, 2012).

Bootstrapped Re-Analysis

As noted earlier, a total of 21 samples met eligibility criteria for the re-analysis. These samples were not evenly divided between the age bands used to categorize the studies in the qualitative synthesis: preschool ($k = 2$), school-age ($k = 8$), adolescent ($k = 2$), adult ($k = 5$), and older adult ($k = 4$). Due to the wide span of ages, the samples were stratified into two samples with 16 years of age as the cut point, where 10 samples were considered adult (i.e., >16 years of age) and 11 samples were considered child and adolescent (i.e., ≤16 years of age). Among the child/adolescent studies, the choice was made to exclude the 2 re-analyzed preschool samples from the calculation of summary statistics for that age range (e.g., mean/median percent convergence, mean/median percent meeting fit criteria). This decision was based on (a) the observation that no separate shifting factor was observed for preschool samples in the qualitative synthesis, (b) the extensive literature detailing the early childhood years as unique and fundamental for executive function development (Müller & Kerns, 2015), and (c) the conceptualization of shifting as an ability that arises later in executive function development (Garon et al., 2008). The exclusion of the preschool samples led to 9 child/adolescent samples with an average age span ranging from 8.33 to 14.41 years. The age span for the adult studies ranged from 17.30 to 72.24. The 17-year-old sample (Friedman et al., 2011) was included with the other adult sample due to factor analytic research observing stability of the structure of executive functions from this age into early adulthood (Friedman et al., 2016). Older adults were included within this age band because (a) there was an insufficient number older adult studies to compose its own group; and (b) although there is evidence for age-related declines in performances on executive function tasks (Reynolds & Horton, 2008), the qualitative findings did not provide definitive evidence for de-differentiation. Unlike the preschool age band, all

three constructs were represented among this age group, and the oldest sample evaluated

produced a three-factor solution (Vaughan & Giovanello, 2010).

       Percent convergence. Provided in the Supplementary Materials, Tables S3 and S4 list

the percentage of models that converged among the 5,000 bootstrapped samples for each

measurement model specified for child/adolescent and adult studies, respectively. The percent

convergence is presented for each individual study, and a mean and median percent convergence

is presented for all studies. These summary statistics for percent convergence are visually

presented in Figures 3a and 4a for child/adolescent and adult studies, respectively. For both the

child/adolescent and adult studies, the rates of convergence were related to model complexity,

where models with more parameters tended to properly converge less often; however, the more

complex set of models differed across age spans in terms of their frequency of convergence. For

example, among adult studies, there was a clear negative relationship between percent

convergence and model complexity. The bifactor model converged the least often ($\bar{x} = 24\%$; *Mdn*

$= 10\%$). The nested factor ($\bar{x} = 57\%$; *Mdn* $= 53\%$) and three-factor models ($\bar{x} = 45\%$; *Mdn* $=$

40%) converged infrequently and less often than the three two-factor models, which all

converged at roughly the same rate: inhibition-shifting merged ($\bar{x} = 76\%$; *Mdn* $= 86\%$),

inhibition-updating merged ($\bar{x} = 71\%$; *Mdn* $= 77\%$), and shifting-updating merged ($\bar{x} = 65\%$;

Mdn $= 66\%$). The unidimensional model converged for almost every bootstrapped sample ($\bar{x} =$

95%; *Mdn* $= 99\%$).

       In contrast to the adult studies, the frequency of convergence among the child/adolescent

samples was slightly different, where the model that converged the least often was the three-

factor model ($\bar{x} = 36\%$; *Mdn* $= 26\%$), while the nested factor ($\bar{x} = 59\%$; *Mdn* $= 60\%$) and bifactor

models ($\bar{x} = 48\%$; *Mdn* $= 49\%$) converged at closer frequencies. For the three two-factor models,

the models merging the shifting factor tended to converge more often. The inhibition-shifting

merged ($\bar{x} = 76\%$; *Mdn* = 89%) and shifting-updating merged models ($\bar{x} = 71\%$; *Mdn* = 56%)

converged more often than the inhibition-updating merged model ($\bar{x} = 59\%$; *Mdn* = 55%). As

with the adult studies, the unidimensional model converged for almost every bootstrapped

sample ($\bar{x} = 97\%$; *Mdn* = 100%).

<div align="center">[INSERT FIGURE 3 ABOUT HERE]</div>

Percent of converged models meeting fit criteria. Tables S3 and S4, in the

Supplementary Materials, list the percentage of the converged models that met lenient and strict

fit thresholds for each measurement model specified for child/adolescent and adult studies,

respectively. The trend in terms of meeting fit thresholds was generally in the opposite direction

of model convergence, where the more complex models tended to fit better than the simpler

models. This was true for both the CFI and RMSEA, and the trend is visually represented in

Figures 3b and 4b for child/adolescent and adult studies, respectively. As also clearly

demonstrated by these figures, the strict fit thresholds were rarely met for most models, whereas

the lenient fit thresholds, though met more often, were still met infrequently.

For the adult studies, the bifactor model met lenient (CFI: $\bar{x} = 63\%$; *Mdn* = 55%;

RMSEA: $\bar{x} = 61\%$; *Mdn* = 60%) and strict fit criteria (CFI: $\bar{x} = 36\%$; *Mdn* = 30%; RMSEA: $\bar{x} =$

25%; *Mdn* = 25%) the most often among the bootstrapped samples for which this model

converged. The nested factor model met lenient (CFI: $\bar{x} = 54\%$; *Mdn* = 52%; RMSEA: $\bar{x} = 59\%$;

Mdn = 58%) and strict fit criteria (CFI: $\bar{x} = 23\%$; *Mdn* = 18%; RMSEA: $\bar{x} = 18\%$; *Mdn* = 14%) at

roughly the same rate that the three-factor model met lenient (CFI: $\bar{x} = 48\%$; *Mdn* = 44%;

RMSEA: $\bar{x} = 57\%$; *Mdn* = 57%) and strict fit criteria (CFI: $\bar{x} = 19\%$; *Mdn* = 10%; RMSEA: $\bar{x} =$

16%; *Mdn* = 15%). The two-factor models all met the fit criteria at about the same frequency,

although the inhibition-updating merged model met the ≤.08 RMSEA criterion ($\bar{x}$ = 42%; *Mdn* = 45%) at a greater rate than the other two-factor models, as made visually evident by a peak in the forest plot line in Figure 4b.

For the child/adolescent studies, the bifactor met lenient (CFI: $\bar{x}$ = 64%; *Mdn* = 71%; RMSEA: $\bar{x}$ = 50%; *Mdn* = 52%) and strict fit criteria (CFI: $\bar{x}$ = 39%; *Mdn* = 42%; RMSEA: $\bar{x}$ = 21%; *Mdn* = 21%) the most often among the bootstrapped samples for which this model converged. The three-factor model tended to meet lenient and strict fit criteria at about the same frequency as the nested factor model. Similarly, the two-factor models all tended to meet lenient and strict fit criteria at roughly the same rate, while the unidimensional model met lenient (CFI: $\bar{x}$ = 36%; *Mdn* = 48%; RMSEA: $\bar{x}$ = 32%; *Mdn* = 21%) and strict fit criteria (CFI: $\bar{x}$ = 11%; *Mdn* = 6%; RMSEA: $\bar{x}$ = 11%; *Mdn* = 5%) the least often.

The percent of converged samples meeting fit thresholds cannot be properly understood without appreciating the percent of models converging among the bootstrapped samples. Those models that did not converge did not provide fit indices to contribute to this overall estimate, indicating that the percent of fitting model based on fit thresholds alone may over-estimate how often these models were accepted among the 5,000 bootstrapped samples. In turn, the next section presents how often models both converged and met fit criteria among the 5,000 bootstrapped samples across studies.

[INSERT FIGURE 4 ABOUT HERE]

Rate of model acceptance based on percent of models both converging and meeting fit criteria. Among the 5,000 bootstrapped samples for each study, the frequency at which models both converged and met fit criteria was quite low across different models estimated, although some models tended to be accepted more often than others. The percent of samples for

which a specified model both converged and met fit criteria is provided for multiple fit thresholds in Tables S3 and S4 within the Supplementary Materials for children/adolescent and adult samples, respectively. Figures 3c and 4c offer a visual representation of these values. These values constitute the percent of samples in which this model would be accepted by a researcher, in that the model both properly converged and met criteria indicative of good model fit.

Among the adult studies, the rate at which models were deemed acceptable was quite low based on lenient fit criteria and extremely low based on strict fit criteria. The nested factor model was the most often accepted model based on both the lenient (CFI: $\bar{x}$ = 41%; Mdn = 26%; RMSEA: $\bar{x}$ = 42%; Mdn = 27%) and strict fit indices (CFI: $\bar{x}$ = 17%; Mdn = 10%; RMSEA: $\bar{x}$ = 13%; Mdn = 6%). Based on lenient fit indices, the three-factor model was the second most often accepted model (CFI: $\bar{x}$ = 25%; Mdn = 13%; RMSEA: $\bar{x}$ = 32%; Mdn = 19%); however, based on strict fit indices, the bifactor model (CFI: $\bar{x}$ = 11%; Mdn = 4%; RMSEA: $\bar{x}$ = 8%; Mdn = 3%) was accepted at about the same frequency as the three-factor model (CFI: $\bar{x}$ = 8%; Mdn = 5%; RMSEA: $\bar{x}$ = 7%; Mdn = 4%). The two-factor models did not differ from the three-factor model or each other in how often they were accepted based on strict fit criteria; however, based on lenient fit criteria, the inhibition-updating merged model was the most often accepted of the two-factor models (CFI: $\bar{x}$ = 19%; Mdn = 10%; RMSEA: $\bar{x}$ =36%; Mdn = 31%). The acceptance rate based on RMSEA was slightly higher for this model compared to the three-factor model, but the three-factor model was accepted more often based on CFI. The unidimensional model was comparable to the two-factor models in terms of strict fit criteria, and was very rarely accepted based on lenient fit criteria as well (CFI: $\bar{x}$ = 8%; Mdn = 0%; RMSEA: $\bar{x}$ = 13%; Mdn = 3%).

The child/adolescent studies did not follow the same trend as the adult studies. As clearly presented in Figure 3c, no model stood out as the most often accepted. Instead the inverse

occurred, where two models were more frequently *not* accepted, specifically – based on lenient

fit criteria – the inhibition-updating merged model (CFI: $\bar{x}$ = 20%; *Mdn* = 20%; RMSEA: $\bar{x}$ =

13%; *Mdn* = 12%) and the three-factor model (CFI: $\bar{x}$ = 21%; *Mdn* = 10%; RMSEA: $\bar{x}$ = 11%;

Mdn = 8%) rarely converged and met fit thresholds. Based on lenient fit criteria, there was no

clear delineation between the unidimensional (CFI: $\bar{x}$ = 36%; *Mdn* = 48%; RMSEA: $\bar{x}$ = 32%;

Mdn = 21%), shifting-updating merged (CFI: $\bar{x}$ = 35%; *Mdn* = 31%; RMSEA: $\bar{x}$ = 25%; *Mdn* =

32%), inhibition-shifting merged (CFI: $\bar{x}$ = 34%; *Mdn* = 32%; RMSEA: $\bar{x}$ = 27%; *Mdn* = 30%),

nested factor (CFI: $\bar{x}$ = 31%; *Mdn* = 26%; RMSEA: $\bar{x}$ = 21%; *Mdn* = 18%), or bifactor models

(CFI: $\bar{x}$ = 28%; *Mdn* = 23%; RMSEA: $\bar{x}$ = 20%; *Mdn* = 22%). There was a bit more of a

distinction based on strict fit criteria, where the nested factor (CFI: $\bar{x}$ = 17%; *Mdn* = 13%;

RMSEA: $\bar{x}$ = 7%; *Mdn* = 4%) and bifactor models (CFI: $\bar{x}$ = 16%; *Mdn* = 13%; RMSEA: $\bar{x}$ = 8%;

Mdn = 9%) were more often accepted based on CFI, but this trend was not evident based on the

RMSEA, which takes model complexity into account.

Model selection based on ΔCFI and ΔRMSEA comparisons. For child/adolescent and

adult samples, respectively, Tables S5 and S6 in the Supplementary Materials provide the

percent model selection (i.e., the frequency at which a model converged and was selected among

5,000 bootstrapped samples) and the percent contingent model selection (i.e., the frequency at

which a model was selected among samples where the model converged). These findings are

presented visually in Figures 5 and 6 for child/adolescent and adult samples, respectively.

Among the adult studies, the rate at which models both converged and were selected was

quite low. Figure 6a illustrates two peaks around the unidimensional and nested factor models.

Based on both the lenient and strict ΔRMSEA cutoffs, which penalizes for model complexity, the

unidimensional model showed the highest frequency of model selection (Lenient ΔRMSEA: $\bar{x}$ =

26%; *Mdn* = 16%; Strict ΔRMSEA: $\bar{x}$ = 32%; *Mdn* = 27%). However, based on the ΔCFI cutoffs,

the rates of selection of the unidimensional model were much lower (Lenient ΔCFI: $\bar{x}$ = 13%;

Mdn = 4%; Strict ΔCFI: $\bar{x}$ = 15%; *Mdn* = 5%). The nested factor model was most preferred based

on ΔCFI cutoffs (Lenient ΔCFI: $\bar{x}$ = 30%; *Mdn* = 21%; Strict ΔCFI: $\bar{x}$ = 26%; *Mdn* = 20%);

however, based on ΔRMSEA cutoffs, the nested factor model was less preferred than many more

parsimonious models, including the three-factor model, a pair of two-factor models (i.e.,

inhibition-updating merged and inhibition-shifting merged), and the unidimensional model.

As shown by a peak in Figure 6b, based on ΔCFI cutoffs, the nested factor (Lenient

ΔCFI: $\bar{x}$ = 57%; *Mdn* = 61%; Strict ΔCFI: $\bar{x}$ = 53%; *Mdn* = 59%) and bifactor models (Lenient

ΔCFI: $\bar{x}$ = 55%; *Mdn* = 62%; Strict ΔCFI: $\bar{x}$ = 49%; *Mdn* = 52%) were the most frequently

selected among samples where those models converged. The ΔRMSEA cutoffs, which penalize

for model complexity, did not show this same preference for the nested factor or bifactor models.

Based on ΔRMSEA cutoffs, the unidimensional, inhibition-updating merged, inhibition-shifting

merged, three-factor, and nested factor models all showed similar frequencies of contingent

model selection.

Among the child/adolescent studies, there was a clear peak in Figure 5a based on

ΔRMSEA cutoffs, evidencing support for the unidimensional model (Lenient ΔRMSEA: $\bar{x}$ =

46%; *Mdn* = 31%; Strict ΔRMSEA: $\bar{x}$ = 53%; *Mdn* = 43%). For the ΔCFI cutoffs, the peak was

not as prominent (Lenient ΔCFI: $\bar{x}$ = 21%; *Mdn* = 9%; Strict ΔCFI: $\bar{x}$ = 26%; *Mdn* = 10%), but

still evidenced a higher rate of model selection compared to all other models. In terms of

contingent model selection, the results were slightly different. As shown in Figure 5b, there was

again a peak based on ΔRMSEA cutoffs, evidencing support for the unidimensional model

(Lenient ΔRMSEA: $\bar{x}$ = 46%; *Mdn* = 35%; Strict ΔRMSEA: $\bar{x}$ = 54%; *Mdn* = 43%). However,

the ΔCFI cutoffs, which do not penalize for model complexity, showed a peak in contingent

model selection for the nested factor model (Lenient ΔCFI: $\bar{x}$ = 41%; *Mdn* = 38%; Strict ΔCFI: $\bar{x}$

= 42%; *Mdn* = 34%).

Mean fit indices, inter-factor correlations, and inter-item correlations. Available in

the Supplementary Materials, Tables S7 and S8 provide the mean fit indices (i.e., CFI and

RMSEA) and 95% confidence intervals for child/adolescent and adult studies, respectively.

These statistics are based only on the models that converged and provided an estimate of the fit

indices. For all models that converged involving correlated factors, Tables S9 and S10 (see

Supplementary Materials) for child/adolescent and adult studies, respectively, provide the mean

inter-factor correlations and 95% confidence intervals. For studies included in the bootstrap re-

analysis, the mean correlations between indicators was also calculated per each construct from

the observed correlation matrices. These values are also provided in the Supplementary Materials

in Table S11. For updating indicators, the correlations were similar between child/adolescent

studies ($\bar{x}$ = 0.41; *Mdn* = 0.30) and adult studies ($\bar{x}$ = 0.38; *Mdn* = 0.33). For shifting indicators,

the correlations were also similar between child/adolescent ($\bar{x}$ = 0.29; *Mdn* = 0.33) and adult

studies ($\bar{x}$ = 0.30; *Mdn* = 0.26). However, for inhibition indicators, the inter-item correlations

were higher for child/adolescent studies ($\bar{x}$ = 0.29; *Mdn* = 0.26) than adult studies ($\bar{x}$ = 0.16; *Mdn*

= 0.18).

Post-hoc evaluation of publication bias. The re-analysis focused on rates of model

acceptance and selection regardless of which model was originally supported by each individual

study. A post-hoc analysis evaluated the presence of publication bias by examining the rate of

model acceptance among the 5,000 bootstrapped samples for the model originally accepted by

the researchers using their observed sample. This analysis was done using only those studies

with accepted models that corresponded to those seven evaluated in the re-analysis, which resulted in 10 child/adolescent samples and 8 adult samples. Although these values are present in Tables S3 and S4, they are presented in isolation in Table S12 as well (see Supplementary Materials) for the convenience of the reader. Among child/adolescent studies, the rate at which the originally accepted models would be accepted among the 5,000 bootstrapped samples was low using both lenient fit criteria (CFI: $\bar{x} = 36\%$; $Mdn = 43\%$; RMSEA: $\bar{x} = 33\%$; $Mdn = 31\%$) and strict fit criteria (CFI: $\bar{x} = 15\%$; $Mdn = 15\%$; RMSEA: $\bar{x} = 13\%$; $Mdn = 12\%$). Among adult studies, this rate was also low using lenient (CFI: $\bar{x} = 37\%$; $Mdn = 14\%$; RMSEA: $\bar{x} = 44\%$; $Mdn = 32\%$) and strict fit criteria (CFI: $\bar{x} = 10\%$; $Mdn = 5\%$; RMSEA: $\bar{x} = 8\%$; $Mdn = 5\%$).

A similar post-hoc analysis evaluated the frequency of model selection and contingent model selection of the originally supported models reported in published studies, with results summarized in the Supplementary Materials in Table S13. Among child/adolescent studies, the rate at which the originally selected models were preferentially selected among the 5,000 bootstrapped samples was low using both lenient cutoffs (ΔCFI: $\bar{x} = 31\%$; $Mdn = 33\%$; ΔRMSEA: $\bar{x} = 37\%$; $Mdn = 27\%$) and strict cutoffs (ΔCFI: $\bar{x} = 33\%$; $Mdn = 33\%$; ΔRMSEA: $\bar{x} = 37\%$; $Mdn = 21\%$). Among adult studies, this rate was also low using lenient (ΔCFI: $\bar{x} = 38\%$; $Mdn = 34\%$; ΔRMSEA: $\bar{x} = 14\%$; $Mdn = 14\%$) and strict fit cutoffs (ΔCFI: $\bar{x} = 34\%$; $Mdn = 30\%$; ΔRMSEA: $\bar{x} = 8\%$; $Mdn = 7\%$). In terms of contingent model selection, the models were selected at a slightly higher rate among those bootstrapped samples where the originally selected model converged, based on lenient (ΔCFI: $\bar{x} = 52\%$; $Mdn = 56\%$; ΔRMSEA: $\bar{x} = 22\%$; $Mdn = 15\%$) and strict cutoffs (ΔCFI: $\bar{x} = 47\%$; $Mdn = 53\%$; ΔRMSEA: $\bar{x} = 14\%$; $Mdn = 9\%$).

Discussion

The systematic review and re-analysis summarized an extensive body of research

exploring executive functions over the last two decades, identifying a large set of studies

producing fairly consistent findings about the structure of executive functions over the course of

the lifespan. A qualitative synthesis of this research covered sample demographics, test selection,

study quality, model fit, and the frequency at which different constructs and models appeared in

the published literature. The existing literature has the appearance of being quite consistent, but

that appearance is partially due to overlapping samples across studies and potential publication

bias. Complementing the qualitative synthesis, a re-analysis of correlation matrices from a sub-

sample of eligible studies compared seven competing measurement models reported in the

published literature (see Figure 2), attempting to quantitatively identify a best-fitting

measurement model for child/adolescent and adult samples.

Findings from the Qualitative Synthesis

The executive function constructs identified most often included inhibition,

updating/working memory, and shifting; however, the number of constructs represented in

accepted measurement models varied by the age of the sample evaluated. The majority of

samples identified were composed of children and adolescents ($k = 27$), while a smaller portion

of studies involved adults ($k = 9$) and older adults ($k = 8$). In terms of the factor models

supported by eligible studies, there was evidence for increasing multidimensionality of executive

functions over the course of development. Preschool samples were roughly split between a one-

factor and two-factor solution, with no studies identifying a specific shifting factor. School-aged

samples showed more support for a three-factor model than a two-factor model, while the

adolescent samples supported three-factor and nested factor solutions. There was comparable

support for two-factor, three-factor, and nested factor models among adult samples. Two of the

studies producing a two-factor solution among adults did not test a three-factor solution (McVay

& Kane, 2012; Was, 2007), and the other involved two studies and found a three-factor solution

in their second study (Klauer et al., 2010). Combined, these findings indicate a gradual

differentiation of executive functions from preschool into adulthood, and the potential emergence

of a specific shifting factor around school-age to adolescence. This is consistent with some

leading theories relating to the neurodevelopment of executive functions (Bardikoff & Sabbagh,

2017; Garon et al., 2008; Müller & Kerns, 2015).

　　　　Although consistent with developmental theories, the increased multidimensionality in

factor solutions with age could alternatively derive from methodological differences between

child and adult studies; specifically, differences in the number of indicators used per construct in

measurement models. A close re-examination of Tables S1 and S2 in the Supplementary

Materials indicates a greater frequency of factors with just two indicators for child/adolescent

studies in comparison to adult studies. Specifically, among child/adolescent studies, six studies

used just two indicators for inhibition (Duan et al., 2010; Lambek & Shevlin, 2011; Lehto et al.,

2003; Rose et al., 2012; Usai et al., 2014; Xu et al., 2013), six studies used just two indicators for

updating/working memory (Agostino et al., 2010; Duan et al., 2010; Lambek & Shevlin, 2011;

Usai et al., 2014; Willoughby et al. 2012a; Xu et al., 2013), and seven studies used just two

indicators for shifting (Agostino et al., 2010; Duan et al., 2010; Lehto et al., 2003; Monette et al.,

2015; Rose et al., 2012; Usai et al., 2014; Xu et al., 2013). In contrast, among adult studies, three

studies used just two indicators for inhibition (de Frias et al., 2009; Frazier et al., 2015; Klauer et

al., 2010), two studies used just two indicators for updating/working memory (de Frias et al.,

2009; Klauer et al., 2010), and two studies used just two indicators for shifting (de Frias et al.,

2009; Frazier et al., 2015). The fewer tests used to tap into specific constructs likely results from practical issues with data collection, where younger children have greater difficulty completing a longer battery of cognitive tests. However, this practical issue could explain why measurement models for younger samples tend to support unidimensional solutions: an insufficient number of construct-specific tests are administered, which limits the amount of construct-specific variance present in the model.

In terms of the consistency between adult and older adult studies, most older adult studies supported a two-factor solution, but there was also support for a three-factor solution. The three-factor models included inhibition, updating/working memory, and shifting, while the two-factor models either merged two of these factors or dropped one of them from the model. These findings could indicate a slight de-differentiation of abilities with older age; however, no studies supported a one-factor solution, a three-factor solution was supported in the oldest sample evaluated (Vaughan & Giovanello, 2010), and – unlike the preschool age group – all three factors were represented in at least one of the measurement models evaluated within this age band. As well, researchers have yet to evaluate the structure of executive function for a substantial portion of mid-life: none of the samples evaluated had a mean age between 30 and 60 years. In turn, if executive functions do de-differentiate, the representation of ages within the current review is not comprehensive enough to identify the time of life at which this de-differentiation occurs, indicating the need for more research on samples in middle adulthood along with more longitudinal investigations. The only longitudinal study evaluating changes in executive functions among older adults included in this review involved just two time points separated by a three-year interval among adults already aged 55 years and above (de Frias et al., 2009), which is an insufficient study duration to examine this issue. Overall, the results from the

systematic review do not support the de-differentiation of executive functions with older age, with the caveat that there are insufficient longitudinal studies on the structure of executive functions and large gaps in the age spans represented in cross-sectional research.

The qualitative analysis effectively summarizes the previous latent variable research on the structure of executive functions, synthesizing the published findings that have followed the seminal work of Miyake and colleagues (2000). It is clear by the synthesis that the three factors evaluated by this original study (i.e., inhibition, updating/working memory, and shifting) have become the most frequently evaluated constructs within this field of research. The extensive popularity of the three-factor model has offered a scaffold for the many reviews on executive function literature (e.g., Bardikoff & Sabbagh, 2017; Best & Miller, 2010; Best et al., 2009; Collette et al., 2006; Garon et al., 2008; Müller & Kerns, 2015; Niendam et al., 2012), where these three factors are often those most extensively discussed. The qualitative synthesis demonstrates that few researchers have expanded beyond the evaluation of these three factors, with few studies including other posited constructs (e.g., strategic retrieval, access to long-term memory) in their executive function measurement models (Adrover-Roig et al., 2012; Fournier-Vicente et al., 2008). Based on this research synthesis, there seems to be a general acceptance of the original three-factor measurement model (Miyake et al., 2000), with limited research pioneering beyond this set of factors throughout the lifespan. Many of these publications are conceptual replications, and their abundance may result from a publication bias in favor of a highly-cited model that many researchers have accepted as the standard model of the field. Despite these many conceptual replications, there is a merited concern about the replicability of this model, as made clear by the re-analysis.

Findings from the Re-Analysis

      The re-analysis effort aimed to explore how well seven alternative models fit the data across multiple samples and test batteries. The re-analysis results were interpreted in two ways. First, by the rate of model acceptance, which considered the rate at which a model met conventional fit thresholds (i.e., CFI $\geq$ .90/.95; RMSEA $\leq$ .05/.08). This first method only evaluated the rate at which different models would converge and show acceptable fit among the 5,000 bootstrapped samples; it did not directly compare different models based on fit indices. The second interpretation was the rate of model selection. This method compared different models based on differences between their CFI and RMSEA values, determining which models presented with superior fit to other models. These results benefit from an interpretation in combination: model acceptance informs the rate at which a model fits the data, and model selection informs the rate at which a model has superior fit to an alternative model.

      An important caveat regarding model selection is the calculation of two statistics: model selection and contingent model selection. Model selection quantifies the rate at which a model both converges and is selected over all other models among the 5,000 bootstrapped samples. If a model does not converge for a specific sample, it cannot be selected. In contrast, contingent model selection is the rate at which a model is selected over all other models among samples in which that model converges. Among samples where that model converges, the percentage quantifies the rate at which the model is superior to alternative models.

      The most telling findings from this re-analysis was the remarkably low rate at which many published models converged and/or met fit thresholds among bootstrapped samples. Most of the studies included in the systematic review were of good quality (e.g., 80% of studies had a study quality score of $\geq$ 8/11), although very few had sufficient power (e.g., 20% $\hat{\pi} \geq$ .80). The

importance of statistical power in structural equation modeling has high relevance to the interpretation of these findings. Although rarely discussed by researchers publishing executive function measurement models, the power of their models is contingent on sample size, model complexity, and the construct reliability of factors (Gagne & Hancock, 2006; Hancock, 2006; Wolf, Harrington, Clark, & Miller, 2013). Despite these issues, most studies included in the re-analysis had relatively small sample sizes and all tested a complex three-factor measurement model. Further, as observed in previous re-analyses of executive function measurement models, factors within this field often have weak to moderate levels of reliability, suggesting limited construct-specific variance captured by the latent factors (Willoughby et al., 2014). This low reliability results from low inter-item correlations between indicators, which was evident among studies included in the re-analysis (range of mean inter-item correlations: $r = 0.23$ to 0.39).

The low rate of model convergence may derive in part from the low construct reliability of factors included in the models, where a limited amount of true construct variance is present for the factors specified (Gagne & Hancock, 2006). In the current re-analysis, the models that converged the least often on average were those with the most factors. For example, the bifactor converged very rarely among adult samples, because there needed to be sufficient unique variance in the common factor, and all specific factors, to ensure adequate construct reliability and non-zero loadings. Alternatively, it is also possible that the low convergence rate resulted from highly similar loadings among indicators within the same factor, which has also been associated with issues of model identification (Kenny & Kashy, 1992). In the original selection of a nested factor model, the decision to drop the inhibition-specific factor was guided by low loadings onto this factor in the context of a bifactor model (Friedman et al., 2008). Considering the low reliability (Baggetta & Alexander, 2016; Schmidt, 2003) and low inter-test correlations

often observed for executive function tests (Willoughby et al., 2014), the manifest variables

included in the re-analysis could have had limited construct variance related to the factor(s) on

which they loaded (Müller & Kerns, 2015). In turn, during the re-analysis effort, there may be

insufficient construct-specific variance in the data for many of the models to properly converge.

A key question that can derive from these analyses is whether a lack of convergence is

evidence against a true model. As articulated in the previous paragraph, multiple study-related

design components can explain why a model does not properly converge, including sample size,

model complexity, and the reliability of measurement. Although model complexity is associated

with the study design, it is also associated with an underlying hypothesis about the structure of a

construct. In the context of confirmatory factor analysis, study design intersects with the

hypothesized structure of executive functions. This is a key reason why the rates of models

meeting fit thresholds and contingent model selection were calculated, to determine the rates of

model acceptance and selection regardless of convergence. However, considering the extremely

low rates of convergence for some models, an interpretation of solely these values does not take

all relevant information into consideration. For example, the bifactor model converges among

only 24% of adult samples on average, but tends to fit more often than all other models among

samples where it converges: 61 to 63% meet lenient RMSEA and CFI thresholds, respectively.

The bifactor model also has a 49 to 55% rate of contingent model selection based on ΔCFI

cutoffs. However, no published study has accepted the bifactor model, and its low rate of

convergence undermines the support for this model based solely on evaluations of fit, because it

was not replicable in such a large proportion of bootstrapped samples. In turn, rates of

convergence and fit have an interactive relationship, and the rates of model acceptance and

selection offer the most effective method for summarizing this relationship: calculating the rate

at which a model both properly converges and meets conventional fit thresholds or cutoffs.

A clear relationship existed between model complexity and convergence, in that more

complex models converged less often. A relationship was also found between model complexity

and model fit, where more complex models better fit the data. Low construct reliability may

explain the high fit of complex models, where these models overfit the data and show excellent

fit by explaining small amounts of covariation between tasks. When interpreting the re-analysis

findings, these conflicting patterns made model selection a difficult task. While a unidimensional

model almost always converges, it will almost never adequately fit the data among adults. In

contrast, a nested factor model rarely converges, but when it does, it will more often meet

traditional fit thresholds.

The excellent fit, low power, and poor construct reliability evident in published studies

brings into question whether those models that fit well among a specific sample and specific

battery of tests happen to be the models that get published, while other models that do not meet

standard fit cutoffs remain in the file drawer. All published studies included in the qualitative

synthesis reported excellent fit for their models (i.e., CFI $\geq$ .95; RMSEA $\leq$ .06), which provides

no means for a reviewer of the overall literature to preferentially select one model from one

study over an equally well-fitting model from another study. This concern aligns with the general

concern of replicability currently facing psychological science (e.g., Pashler & Harris, 2012;

Pashler & Wagenmakers, 2012; Simmons, Nelson, & Simonsoh, 2011).

A good fitting model captures the data well, but it does not necessarily reflect the true

model for the population (Hancock, 2006). Considering the low power of these excellent fitting

models, the question remains whether they could be replicated among small samples drawn from

the same population. The majority of studies were underpowered and denoted as conceptual replications, rather than direct replications using identical test batteries and recruiting a sufficient sample size. These studies often found similar results to the first measurement model of executive functions (Miyake et al., 2000) despite using a different collection of tests and often an alternative population from which to sample. As with direct replication failures, conceptual replication failures are rarely published (Makel, Plucker, & Hegarty, 2012). In turn, it is possible that the many published studies that contain the most frequently reported factors (i.e., inhibition, updating, and shifting) may be the conceptual replication successes, while the failures not supporting a three-factor model remain in the file drawer.

One significant finding that may go missed from the aggregation of published work was that every published study found evidence for at least one measurement model. There were no studies that attempted to conceptually replicate a measurement model, failed, and published that failure. It is hard to imagine that a journal would eagerly publish a study involving solely a confirmatory factor analysis that did not report any model meeting standard fit thresholds. Considering the heterogeneity of dependent variables across studies, researchers could adjust the indicators included in their model until they find a model that both converges and fits their data, either replacing or removing specific tests or re-analyzing the model with an alternative dependent variable for a given test. This approach would make the results of published studies highly data-driven; and explain, in part, the concerns of non-replicability deriving from the findings of the re-analysis.

A post-hoc analysis shed further light on the issue of publication bias and potential non-replicability within this field. On average, the accepted models reported by researchers were accepted among only around a third to less than half of bootstrapped child/adolescent (i.e., 33 to

36%) and adult samples (i.e., 37 to 44%) based on lenient fit thresholds. In terms of model

selection, the originally selected model was only re-selected among about a third of

child/adolescent samples (i.e., 31-37%) based on lenient cutoffs. The rates of re-selection were

variable for adult samples depending on the use of ΔRMSEA (i.e., 14%) or ΔCFI (i.e., 38%).

The rates of re-selection were only slightly higher based on contingent model selection, again

using lenient cutoffs, among child/adolescent samples (i.e., 42% for both ΔRMSEA and ΔCFI)

and adult samples (i.e., 22% using ΔRMSEA and 52% using ΔCFI).

These findings clearly illustrate a substantial publication bias across studies reporting

measurement models for executive function. This bias affected the results of the re-analysis,

which found low rates of model acceptance and selection for all the models evaluated, although

some models appeared to fit the data or present with superior fit more consistently than others.

Considering the influence of bias, the inference drawn from the re-analysis must be interpreted

with significant caution. Issues of low power indicate that even the most established of models

have weak evidence in aggregate. Further, publication bias may have resulted in the acceptance

and dissemination of many studies that correspond to the widely accepted three-factor

measurement model (Miyake et al., 2000). As articulated in the following section, the adult

research does show modest support for the three-factor or nested factor models (e.g., Friedman et

al., 2008, 2009, 2011, 2016), which could have resulted from researchers designing their studies

around this model – which was apparent based on the qualitative synthesis – and reviewers

preferring this model in their critique of submitted manuscripts. However, despite issues of

publication bias, a primary aim of the re-analysis was to identify a measurement model that best

fit the data across published studies; and the following interpretation of the re-analysis findings

attempts to find a signal within the noise of re-analyzed data.

Re-analysis of adult samples. The published results offer some empirical information

about the nature of executive functions. The statistician George Box once wrote "all models are

wrong, but some are useful," (Box & Draper, 1987, p. 424), which applies well to the current

findings. As made visually clear by a peak in Figure 4c, the most frequently accepted factor

model among adults was the nested factor model; however, this model only converged 57% of

the time on average across samples. Among those samples for which the model converged, only

59% had an RMSEA ≤ 0.08 and only 54% had a CFI ≥ 0.90. In turn, despite being the most often

accepted, the nested factor model would be accepted, based on lenient fit thresholds, among only

41 to 42% of 5,000 bootstrapped samples on average across studies. In regard to model selection,

the nested factor model was the most often selected based on ΔCFI lenient (i.e., 30%) and strict

(i.e., 26%) cutoffs; however, based on ΔRMSEA, which penalizes for model complexity, the

unidimensional model was selected most frequently per lenient (i.e., 26%) and strict (i.e., 32%)

cutoffs. Although these peaks were present, per visual inspection of Figure 6a, they were not

prominent, and alternative models (e.g., the three-factor model based on ΔCFI and the two-factor

models based on ΔRMSEA) had similar rates of model selection. Presented as a peak in Figure

6b, the nested and bifactor models had the highest rates of contingent model selection based on

ΔCFI; however, there was no clearly preferred model based on contingent model selection rates

using ΔRMSEA, although the shifting-updating merged model was essentially never selected.

For the adult studies, three of the highest quality studies accepted the nested factor model

using the same test battery across different samples (Fleming et al., 2016; Friedman et al., 2011;

Ito et al., 2015). The results of these three studies align with the results of the overall re-analysis.

The convergence rate ranged from 89% to 96% and the acceptance rate ranged from 72 to 96%

and 83 to 95% for the lenient thresholds of the CFI and RMSEA, respectively. In terms of model

selection, the nested factor model was selected among 39 to 70% and 10 to 22% of 5,000

bootstrapped samples based on the lenient cutoffs for the ΔCFI and ΔRMSEA, respectively.

Among only those samples where the nested factor model converged, the rates of contingent

model selection were largely similar: 41 to 76% and 11 to 24% of samples based on the lenient

cutoffs for the ΔCFI and ΔRMSEA. Within a small set of consistent studies with well-powered,

similarly aged samples ($\hat{\pi}$ range: 0.74 to 0.99; $\bar{x}$ age range: 17.30 to 22.50), the model

consistently converged and met fit thresholds; however, it was inconsistently selected over

alternative models.

The rates of model acceptance provide some support for the nested factor model among

adult samples; however, when directly comparing different models based on changes in fit, no

model was selected at a significantly greater frequency than other models among adults. When

considering only those sample in which the nested factor model converges, the nested factor

model was only selected at a higher rate based on ΔCFI cutoffs, while the use of ΔRMSEA

cutoffs showed comparable rates of contingent model selection across most other models.

The RMSEA favors parsimonious models (Hooper et al., 2008), and the rates of model

selection and contingent model selection based on ΔRMSEA indicate that more parsimonious

models (e.g., unidimensional and two-factor models) tended to be selected more often than, or at

similar rates to, the nested factor model. This finding could indicate that the nested factor model

is too complex, with limited improvement in fit despite increased model complexity. However,

both rates of model acceptance and model selection must be interpreted in combination. Whereas

ΔRMSEA indicated the highest rate of model selection for the unidimensional model, this model

was essentially never accepted based on conventional fit thresholds. As shown in Figure 4c, the

nested factor model tended to be accepted most often based on lenient thresholds for both the

CFI and RMSEA. In turn, even if the unidimensional model showed superior fit to a more complex model, it was extremely rare for this model to show acceptable fit, and it would not likely be accepted by a researcher evaluating competing models.

In aggregate, these results lend some tentative support for the nested factor model. This finding aligns with the basic premise of the first application of confirmatory factor analysis to executive functions (Miyake et al., 2000): the variance in executive function test batteries tends to show both unity and diversity. Although there is not a clear model that fully explains the precise structure of executive functions, the basic notion of unity and diversity is evident. A method for determining which measurement model ultimately aligns with the true nature of executive functions will require a closer examination of the brain-behavior relationships that underlie the constructs included in the accepted measurement model. Researchers have found brain activity during performance-based tasks of executive functions in areas associated with specific constructs, including the right inferior frontal cortex, basal ganglia, and pre-supplementary motor area activity during inhibition tasks (Aron, 2008), dorsolateral prefrontal cortex activity (DLPFC; Stuss & Levine, 2002) as well as frontopolar activity (Collette et al., 2005) during updating/working memory tasks, and DLPFC and dorsal anterior cingulate cortex activity during shifting tasks (Luna et al., 2015).

Although specific brain-behavior relationships have been proposed, there is evidence for both the unity and diversity of brain activity underlying separate executive function constructs (Collette et al., 2005, 2006). A comprehensive meta-analytic investigation (Niendam et al., 2012) found strong evidence for a superordinate fronto-cingulo-parietal network that showed common activity during tasks tapping into inhibition, working memory, and flexibility (i.e., a term often used synonymously with shifting; Baggetta & Alexander, 2016). This integrative function could

parallel the common factor present in the nested factor model, which past researchers have conceptualized as the ability to "actively maintain task goals and goal-related information and use this information to effectively bias lower-level processing" (Miyake & Friedman, 2012, p. 11), arguably necessary for successful performance across executive function domains. Despite the alignment of the re-analysis findings and brain-behavior research, the results do not identify a definitive measurement model of executive function in adulthood. Considering issues of low power and publication bias, the findings are tentative, and require further scrutiny in future studies before any definitive model of executive function among adults can be unequivocally accepted.

Re-analysis of child/adolescent samples. In comparison to the findings among adult samples, the results of the re-analysis of the child/adolescent samples were interpretable in the opposite fashion. Whereas for the adult studies in Figure 4c, there was a clear peak in model acceptance rates for the three-factor and nested factors models, the child/adolescent studies in Figure 3c had two definitive "valleys" for the inhibition-updating merged and three-factor models, evidencing that models with differentiated shifting factors were *less* preferable to models that either merged the shifting factor or had a strong common executive function bifactor. This trend is consistent with discussion of a non-differentiated shifting factor early in development (Garon et al., 2008) and the notion that an independent shifting ability emerges later in development (Müller & Kerns, 2015). This trend was observed despite removing preschool samples from the means and medians calculated in the re-analysis.

The competing child/adolescent models that both converged and exceeded lenient fit thresholds most often were the unidimensional, shifting-updating merged, inhibition-shifting merged, nested factor, and bifactor models. While these models were not easily differentiated

based on the lenient CFI cutoff, the lenient RMSEA cutoff was met most often for the

unidimensional ($\bar{x}$ = 32%; *Mdn* = 21%), the shifting-updating ($\bar{x}$ = 25%; *Mdn* = 32%), and

inhibition-shifting models ($\bar{x}$ = 27%; *Mdn* = 30%). Considering the greater complexity of the

nested factor and bifactor models, the more parsimonious models were favored by the RMSEA

cutoff. As with the adult studies, there was not a clear determination about which model should

be preferred based on fit indices; however, the re-analysis of child/adolescent samples supported

(a) either a unidimensional or two-factor solution and (b) a model that does not have a

differentiated shifting factor.

In comparison to the rates of model acceptance, the model selection analysis showed a

clear peak in selection rates based on ΔRMSEA cutoffs in favor of the unidimensional model

(i.e., 46 to 53% of samples), as shown visually in Figure 5a. Figure 5b shows this same peak for

contingent model selection based on ΔRMSEA cutoffs (i.e., 46 to 54% of samples). Minimal

differences in rates of model selection and contingent model selection were due to the mean 97%

convergence rate of the unidimensional model. Contingent model selection did show a peak in

favor of the nested factor model based on ΔCFI cutoffs (i.e. 27 to 30% of samples); however, this

model was a distant second in rates of contingent selection based on ΔRMSEA cutoffs, and a

more parsimonious interpretation would support a simpler unidimensional model. A comparison

between Figures 3c and 5a showed the same pattern of valleys, where models with

undifferentiated shifting factors tended to be selected at greater rates.

In combination, the results of the model acceptance and selection analyses lend the most

support for a unidimensional model among the child/adolescent samples; however, this model

was not accepted unequivocally, and two-factor models with an undifferentiated shifting factor

had some modest levels of support as well. This non-differentiated system is supported by

neurodevelopmental trajectories, where grey matter in the DLPFC, which is associated with both updating/working memory and shifting (Luna et al., 2015; Stuss & Levine, 2002), is pruned after the ventral frontal regions associated with inhibition (Aron, 2008) during child and adolescent development (Müller & Kerns, 2015). As with the adult findings, low power across these studies resulted in overall low rates of convergence and few models meeting traditional fit thresholds. In turn, these findings require a cautious interpretation; however, the conclusions are fairly conservative, and consistent with previous theories of executive function development (Bardikoff & Sabbagh, 2017; Garon et al., 2008).

Limitations

This systematic review and re-analysis offers the first comprehensive and empirical summary of measurement models for executive function test batteries across the lifespan. Despite the comprehensiveness of this review, the conclusions drawn from it remain tentative due to a variety of limitations. A first limitation pertains to the limited diversity of the samples evaluated. The eligible samples were largely balanced in gender (i.e., 52.56% female); however, the samples were not diverse in terms of their ethnic and racial composition. Ethnic or racial demographics were only reported for about 40% of samples, with clear discrepancies across age ranges in terms of how often this information was reported. Although 66% of preschool samples had racial or ethnic makeup reported, only 25% of older adult studies provided similar information. There were some studies with specifically Chinese samples (Duan et al., 2010; Lee et al., 2012; Xu et al., 2013) or majority minority samples (Masten et al., 2012; Rose et al., 2012); however, these few ethnically and racially diverse samples were exclusively child and adolescent.

Based on reported demographics, the adult and older adult samples were not only mostly White, but were also highly educated. Over half of the adult samples were undergraduate populations, while the older adults ranged in education from 11.30 to 17.67 years, with all but one sample having over 15 years of education on average. Based on the sample demographics, the generalizability of this research to diverse populations remains questionable. Furthermore, although the mean ages ranged from 3.01 to 73.68 across samples, there was still a gap in the representation of middle adulthood. As noted earlier, no researchers reported a sample with a mean age between 30 and 60. In turn, the structure of executive functions within middle adulthood remains largely unevaluated, because most studies categorized as adults in this review evaluated an undergraduate or college-aged sample. Future researchers would benefit from recruiting more participants within middle adulthood, without post-secondary education, and from diverse ethnic or racial backgrounds. This would ensure that the research findings on the structure of executive functions are representative beyond a well-educated and White population.

Additional limitations pertained specifically to the re-analysis effort. A primary aim of the re-analysis was to determine which published measurement model best fit summary data across studies; however, the results did not identify a best model, but rather showed modest levels of evidence for a small selection of models. Rates of model acceptance were overall quite low, even for the most often accepted model. Further, direct comparisons between models did not demonstrate a single model being accepted unequivocally. A reason for this finding may have resulted from the bootstrapping method, which cannot control for certain limitations of individual studies (e.g., low power, poor construct reliability). While a meta-analytic confirmatory factor analysis more effectively controls for these limitations when aggregating information across studies, this method relies on a pooled correlation matrix (Cheung & Chan,

2005), which requires the same variables to be used across different studies. Unfortunately, only a very small number of studies had the same set of manifest variables, thus impeding the use of a traditional meta-analytic approach. An assumption of confirmatory factor analysis is that the manifest variables are inter-changeable, which has led the field of executive function measurement models to include numerous different combinations of variables posited to tap into different constructs. The bootstrap method used here allowed for the synthesis of findings across studies using different test batteries, but every bootstrap iteration carries with it the individual limitations of the original empirical study. However, from another perspective, this apparent limitation did provide insight into the process of decision making at the modeling stage: simple models converge more often, but fail to fit the data well; while complex models hardly converge, but if they do, they tend to fit well. This resulted in just a small number of models that made it through the vetting process, and it explains the situation in this field, where a multitude of different factor structures tend to emerge, but each one of them is difficult to replicate.

Some analytical decisions and assumptions may also limit the interpretation of the current findings. In the re-analysis effort, residual correlations between tests were not specified, and no model modifications were considered. Such residual correlations or modifications could resolve issues of non-convergence or poor fit, and are often included for justifiable reasons in research practice. Conceptually, if each model for each of the 5,000 bootstrapped samples was closely examined, some model modifications could have allowed models to converge or improve fit; however, a model-by-model assessment at this level was not possible considering the magnitude of simulated samples and models evaluated, and this method could have resulted in the aggregation of fairly incomparable models depending on the extent of modifications needed for each model in individual samples. Another analytical decision that serves as a potential

limitation was the wide age ranges used for both the child/adolescent ($\bar{x}$ age range: 8.33 to 14.41)

and adult samples ($\bar{x}$ age range: 17.30 to 72.24). This decision limited inference about the

structure of executive functions at specific points in human development (e.g., childhood vs.

adolescence, young vs. older adulthood). Collapsing across developmental periods ensured a

roughly equal number of samples fell within the child/adolescent ($k = 9$) and adult ($k = 10$) age

spans prior to calculating a mean and median for rates of convergence and model acceptance.

Developmental considerations were taken prior to calculating means and medians during the re-

analysis, such as excluding preschool samples due to a non-differentiated shifting factor (Miller

et al., 2012; Usai et al., 2014). Despite wide age bands, conclusions based on a larger collection

of samples arguably allow for more accurate inference about the structure of executive functions

during development and adulthood.

Another limitation of the systematic review was the lack of individual participant data,

because the findings presented in the re-analysis were based solely on simulated data using

correlation matrices. Non-parametric bootstrapping with re-sampling is a more common method

used by researchers with their raw datasets, but was not possible using summary data. If

researchers were to use non-parametric bootstrapping with re-sampling to re-analyze their own

sample data, the conclusions may differ from those amalgamated in the current review. In the

context of the re-analysis, the parametric bootstrapping simulates samples of the same N as the

observed samples, pulled from an assumed multivariate normal distribution. The alternative non-

parametric bootstrapping with re-sampling approach more commonly used with raw data would

not make this assumption; and software packages commonly used for confirmatory factor

analysis would not offer a confidence interval around fit indices, nor a rate at which simulated

samples met fit cutoffs. However, some software packages (e.g., MPlus; Muthén & Muthén,

2014) would quantify the number of bootstrapped draws completed, which would give an estimate of how often the model would properly converge. The use of bootstrapping may be fruitful for future researchers to guide their model selection, allowing them to determine the frequency at which an excellent fitting model would replicate among a set of bootstrapped samples.

Future Directions in Research on Executive Functions

In terms of future directions for researchers evaluating measurement models of executive functions, many gaps in the field remain unresolved based on the current review. As is clear from the findings, the results provided some guidance regarding which models have the most – or least – empirical support, but they did not suggest that any model should be unequivocally accepted. Future researchers should evaluate alternative models including factors not previously represented in published measurement models. Despite some inconsistencies in the naming of factors, most researchers have taken the approach of evaluating the three-factor model (i.e., inhibition, updating, and shifting; Miyake et al., 2000), which has substantially influenced their test selection and design. The field of executive function measurement models shows a broad acceptance of the three-factor model, or the more recently proposed nested factor model of Miyake and Friedman (2012); however, the current findings raise serious doubts about the replicability of both of these models. Although there have been many conceptual or direct replications of these models (e.g., Lehto et al., 2003; de Frias et al., 2009; Fleming et al., 2016; Ito et al., 2015; Klauer et al., 2010), the re-analysis indicated only modest evidence for either of these models in aggregate. To move the field forward, researchers must continue to conduct high-powered studies to further evaluate and compare the replicability of these models, or

include the assessment of new models or executive function factors not often evaluated by previous researchers.

Just a small set of studies explored additional constructs (e.g., Access to Long Term Memory, Adrover-Roig et al., 2012; Hot and Cool Executive Function, Carlson et al., 2014; Strategic Retrieval, Fournier-Vicente et al., 2008). Future researchers should consider exploring new constructs that have been postulated in previous research, but not consistently evaluated in confirmatory factor analyses, such as planning, problem solving, fluency, and reasoning (Packwood et al., 2011). As well, factor analytic studies not covered in this review have explored the multidimensionality of specific executive function constructs (e.g., inhibition, Aichert et al., 2012, Friedman & Miyake, 2004; problem solving, Cinan et al., 2013; Scherer & Tiemann, 2014), indicating that sub-components under the umbrella term of executive functions may be umbrella terms within themselves and worth further exploration.

In addition to the measurement of different constructs, other methods for advancing the field could include evaluating previously untested measurement models, re-analyzing primary datasets, or adding longitudinal follow-ups to research designs. Since the systematic search was conducted, one study evaluated a second-order factor model of executive functions (Wolff et al., 2016) and another tested a bifactor model that examined the differentiation of executive functions from fundamental cognitive abilities over the preschool years (Nelson et al., 2016). One recent re-analysis explored a formative factor model as an alternative method of both modeling and interpreting performances on tests of executive functions (Willoughby & Blair, 2016). While a formative model simply flips the directional path between manifest variables and factors (Kline, 2006), other re-analyses could conceptualize executive functions in a more causal manner. If conceptualizations of executive functions in early childhood suggest that inhibition

and updating precede shifting development (Garon et al., 2008), then an alternative model could use causal paths, where shifting is endogenous to inhibition and updating in a structural equation modeling framework. In terms of longitudinal follow-up, only a small set of studies have evaluated longitudinal invariance of executive function factors (e.g., de Frias et al., 2009; Friedman et al., 2016; Lee et al., 2013; Willoughby et al., 2012b), and future longitudinal research designs may clarify which factor structures are stable and replicable over time.

Future researchers would also benefit from conducting *a priori* power analyses before to testing measurement models (Hancock, 2006), helping determine the necessary sample size to conduct their analysis. The systematic review clearly evidenced the issue of power endemic within this field, and future small-scale studies that do not consider power in their research design may ultimately be non-replicable. Any consumer of executive function research should be mindful of inferences drawn from underpowered studies with complex models explaining weak inter-item correlations, and future researchers within this field should explicitly address sample size, model complexity, and construct reliability as they relate to the power of their measurement model. This recommendation is not to dissuade researchers from conducting future confirmatory factor analyses on executive function test batteries, but rather to emphasize the importance of ensuring those future studies have the power to produce accurate and replicable findings.

When considering future small-scale studies, the consistency of the tests used to measure executive functions is of the utmost importance. The field must move towards a more consistent use of common tests with greater reliability to ensure that published measurement models are directly comparable and include factors with sufficient shared variance between manifest variables. While some tests were used consistently (e.g., the Stroop task, Antisaccade, *n*-back), a post-hoc exploration of the Stroop paradigms identified inconsistencies in the dependent

variables that were derived from Stroop tests and ultimately used as indicators in measurement

models. There were six different dependent variables deriving from Stroop paradigms among

child/adolescent studies, as well as six different dependent variables deriving from Stroop

paradigms among adult studies. Differences in the dependent variables deriving from specific

tasks can potentially account for different results across studies. While this evaluation of

dependent measures was a post-hoc exploration based on the published literature, it evidences

the need for a close evaluation of the methods through which researchers measure executive

functions in latent variable studies. An assumption of confirmatory factor analysis is that the

manifest variables are interchangeable; however, different scores from the same test rarely

correlate perfectly, and will have different relationships with other indicators and the latent

factor. Thus, deciding on the tests used to measure specific constructs, and the scores used to

operationalize these constructs, can have a substantial influence on the convergence and fit of a

measurement model. The last review on the instruments used to assess executive functions

occurred roughly a decade ago (Chan et al., 2008), and the current review provides a scaffold

through which a closer examination of both executive function tests and scores can be evaluated.

While the tests used by researchers vary by population (e.g., young children complete simpler

paradigms than young adults), differences in the dependent variables deriving from these tests

have not been explored. The post-hoc assessment of the Stroop test alluded to notable variability

in the dependent measures used by different researchers examining different age groups.

Conceptually, if researchers systematically differ in their preferred dependent variables (e.g.,

accuracy, reaction time, or a time-to-accuracy ratio), this methodological difference could

explain some of the variability in the results observed across studies, and a closer examination of

heterogeneity in dependent measures moving forward could further the argument for greater

consistency in executive function measurement.

Aside from variability in the exact scores used across confirmatory factor analyses, there

was substantial variability in the batteries used across studies as well. Concerns about the

heterogeneity between studies in how specific constructs are measured has been raised by

previous reviewers of executive function research (Bardikoff & Sabbagh, 2017; Müller & Kerns,

2015). Although there is some consistency in the indicators assigned to different constructs, few

studies had the exact same test battery, which could explain the inconsistencies in factor

solutions and inter-factor correlations across different studies. Three of the highest quality

studies were based on a common test battery (Fleming et al., 2016; Friedman et al., 2011; Ito et

al., 2015), and all three accepted the nested factor model. The factor structure of this battery has

also been evaluated longitudinally, showing stability in its structure over a 6-year period

(Friedman et al., 2016).

The evaluation of executive functions in clinical practice is similarly disparate (Rabin et

al., 2016). Since the first published measurement model on executive function, there has been a

push for the translation of latent variable research into clinical practice (Miyake, Emerson, &

Friedman, 2000), but practitioners do not often use composite scores of executive functions in

their assessments. The continued evaluation of executive functions in both academic and clinical

settings will require consistent measurement in order to provide comparable and interpretable

results; however, any consensus in regards to its measurement would likely require an updated

review of the many tests used to measure specific constructs to date (Chan et al., 2008), and a

gathering of top researchers in the field to arrive at a preferred battery with a strong

psychometric foundation to rationalize its widespread use (Baggetta & Alexander, 2016). The

use of a common battery could overcome some of the shortcomings of individual studies

evidenced by this review. A common battery would facilitate data sharing, and a data repository

of common elements across studies would overcome issues of low power at the individual study

level. Some researchers have attempted to produce batteries for widespread dissemination. The

National Institute of Health funded the development of a test battery for the assessment of

executive functions in clinical trials (i.e., Executive Abilities: Measures and Instruments for

Neurobehavioral Evaluation and Research, EXAMINER; Kramer et al., 2014), providing factor

scores for working memory, fluency, cognitive control, and a global composite, which align at

least partly with the factors supported by the re-analysis of adult samples.

Conclusions

The systematic review and re-analysis offers the first comprehensive qualitative and

quantitative synthesis of a rich body of latent variable research on executive function

measurement models. This synthesis was conducted with three aims in mind: (a) summarizing

the published evidence for different measurement models of executive functions, (b) identifying

the number of executive function constructs evaluated as factors in previous studies, and (c)

determining a best-fitting measurement model through re-analysis of summary data. The pursuit

of these specific aims led to many relevant conclusions from a close evaluation of the published

literature, as listed below:

- The constructs most often represented in published measurement models of executive
  function include inhibition, updating/working memory, and shifting.
- Published measurement models were most often one to two-factor models among
  preschoolers, three-factor models among school-aged children, three-factor or nested
  factor models among adolescents and adults, and two-factor models among older adults.

- These findings support differentiation of executive functions from preschool into adulthood, with the emergence of shifting during the school-age to adolescent years.

- The results do not offer support for the de-differentiation of executive functions over the course of adulthood, because the oldest sample evaluated produced a three-factor model and much of the adult age span (i.e., 30 to 60 years) is unrepresented in published research.

- For all models evaluated, the re-analysis showed predominantly low rates of model acceptance (i.e., the rate at which a model both converged and met conventional fit thresholds) and model selection (i.e., the rate at which a model converges and shows superior fit to all other models), which likely resulted from issues of low power and poor construct reliability when evaluating fairly complex measurement models.

- The re-analysis provided modest support for a one to two factor model among child/adolescent samples and a nested factor model among adult samples, which suggests greater unity among younger samples and a balance of unity and diversity among adult samples. However, considering low rates of model acceptance and selection overall, these findings are tentative, and no model was accepted unequivocally.

- Future researchers using confirmatory factor analysis should conduct *a priori* power analyses when designing their studies, considering sample size, model complexity, and construct reliability. Underpowered studies with complex models explaining limited shared variance will add non-replicable findings to the field.

- Moving forward, researchers should continue to determine the replicability of the models tested herein through high powered studies, but should also consider alternative models that may take a different approach to conceptualizing executive functions.

Overall these findings are tentative and do not offer definitive conclusions regarding the true nature of executive functions. Alternatively, the findings provided herein offer an affirmation of the "elusive nature of executive functions" (Jurado & Rosselli, 2007, p. 213). Despite its elusive nature, the goals of defining, measuring, and understanding executive functions remain tantamount to psychological research, considering the many clinical and functional outcomes associated with executive functions (e.g., Bell-McGinty et al., 2002; Cahn-Weiner et al., 2002; Espy et al., 2011; Karr, Areshenkoff, & Garcia-Barrera, 2014; Snyder, 2013; Scott et al., 2015) and the interventions already developed to enhance executive functions across the lifespan (e.g., Baggetta & Alexander, 2016; Diamond & Lee, 2011; Karr, Areshenkoff, Rast, & Garcia-Barrera, 2014; Krasny-Pacini, Chevignard, & Evans, 2014).

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Figure 1. Flow Diagram of systematic review

Identification	Records identified through database searching (*n* = 791)
	Additional records identified through other sources (*n* = 33)

Number of records after duplicates removed (*n* = 644)

Screening

Records screened (*n* = 644) → Records excluded (*n* = 507)

Eligibility

Full-text articles assessed for eligibility (*n* = 137)

Full-text articles excluded

- Total: *n* = 98
- No Healthy Sample: *n* = 5
- No/Non-EF CFA: *n* = 59
- <2 indicators from separate tests: *n* = 4
- Non-performance-based tasks in CFA: *n* = 3
- Fewer than 3 EF Tests: *n* = 4
- Shared dataset: *n* = 22

Included

Studies included in qualitative synthesis (*n* = 40)

Studies included in re-analysis (*n* = 17)

Figure 2. Diagrams of factor models tested in the re-analysis
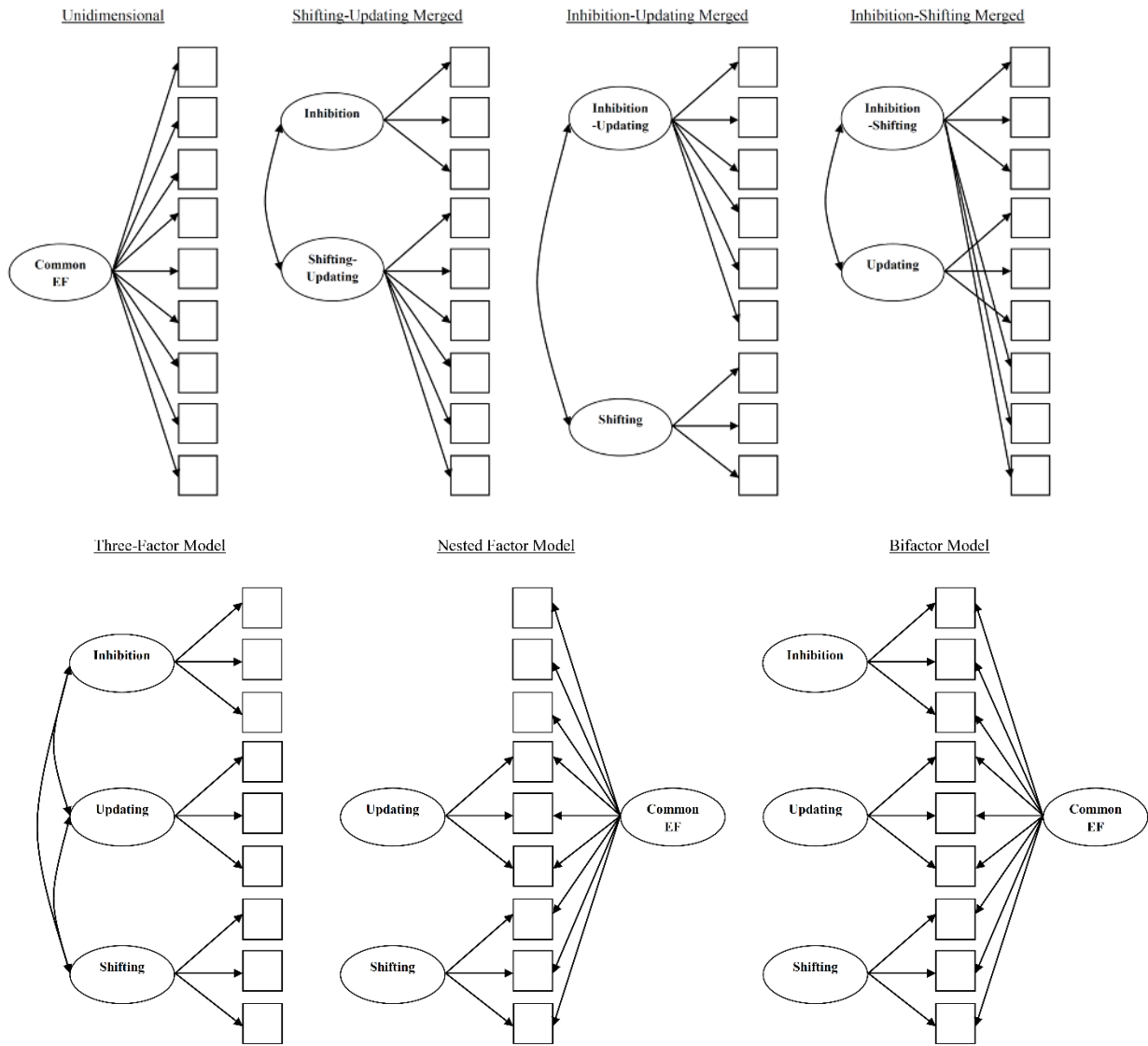
Figure 3. Child and Adolescent Studies: Forest Plots of Percent Convergence, Percent Meeting Fit Criteria, and Percent Both Converging and Meeting Fit Criteria among 5,000 Bootstrapped Samples

(a) Average and Median Percent Convergence among 5,000 Bootstrapped Samples by Measurement Model
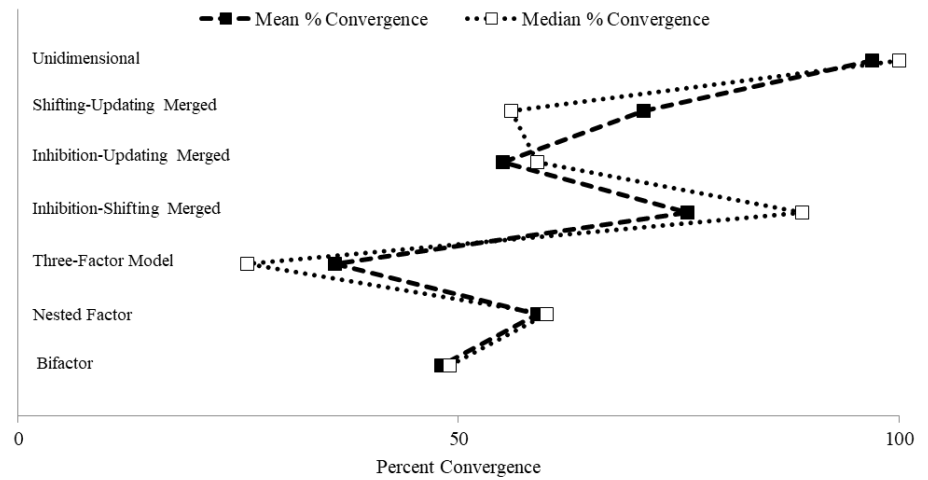
(b) Average Percent of Converged Models Meeting Lenient or Strict Fit Criteria by Measurement Model

(c) Average Percent of Models Both Converging and Meeting Lenient or Strict Fit Criteria by Measurement Model

Note. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; Lenient Fit Criteria = CFI ≥ 0.90 and RMSEA ≤ 0.08; Strict Fit Criteria = CFI ≥ 0.95 and RMSEA ≤ 0.05.

Figure 4. Adult Studies: Forest Plots of Percent Convergence, Percent Meeting Fit Criteria, and Percent Both Converging and Meeting Fit Criteria among 5,000 Bootstrapped Samples

(a) Average and Median Percent Convergence among 5,000 Bootstrapped Samples by Measurement Model
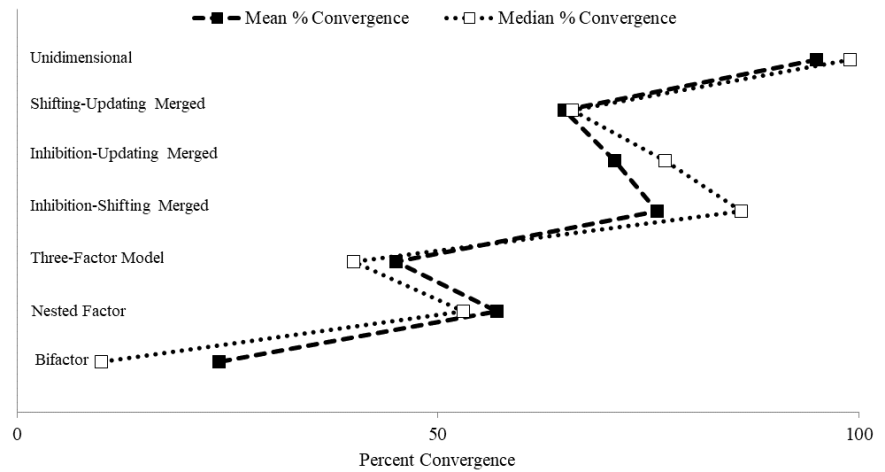
(b) Average Percent of Converged Models Meeting Lenient or Strict Fit Criteria by Measurement Model
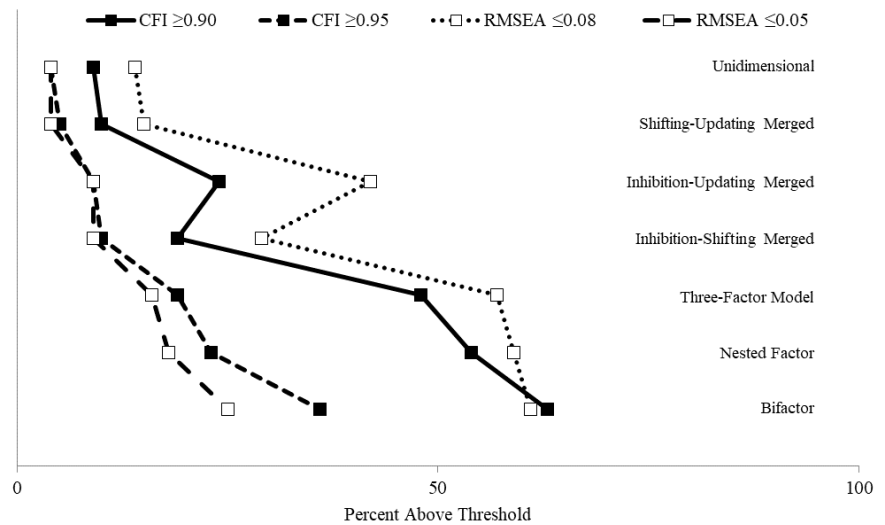
(c) Average Percent of Models Both Converging and Meeting Lenient or Strict Fit Criteria by Measurement Model

Note. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; Lenient Fit Criteria = CFI ≥ 0.90 and RMSEA ≤ 0.08; Strict Fit Criteria = CFI ≥ 0.95 and RMSEA ≤ 0.05.

Figure 5. Child and Adolescent Studies: Forest Plots of the Percent Model Selection and Percent Contingent Model Selection

(a) Percent Model Selection: Average Percent of Bootstrapped Samples where Model Converged and was Selected based on Lenient or Strict ΔCFI or ΔRMSEA Cutoffs

(b) Percent Contingent Model Selection: Among Bootstrapped Samples where the Model Converged, Average Percent of Samples where the Model was Selected based on Lenient or Strict ΔCFI or ΔRMSEA Cutoffs

Note. ΔCFI = Change in Comparative Fit Index; ΔRMSEA = Change in Root Mean Square Error of Approximation; Lenient Change in Fit Cutoffs = ΔCFI ≥ .005 and ΔRMSEA ≤ -.010; Strict Change in Fit Criteria = ΔCFI ≥ .010 and ΔRMSEA ≤ -.015.

Figure 6. Adult Studies: Forest Plots of the Percent Model Selection and Percent Contingent Model Selection

(a) Percent Model Selection: Average Percent of Bootstrapped Samples where Model Converged and was Selected based on Lenient or Strict ΔCFI or ΔRMSEA Cutoffs

(b) Percent Contingent Model Selection: Among Bootstrapped Samples where the Model Converged, Average Percent of Samples where the Model was Selected based on Lenient or Strict ΔCFI or ΔRMSEA Cutoffs

Note. ΔCFI = Change in Comparative Fit Index; ΔRMSEA = Change in Root Mean Square Error of Approximation; Lenient Change in Fit Cutoffs = ΔCFI ≥ .005 and ΔRMSEA ≤ -.010; Strict Change in Fit Criteria = ΔCFI ≥ .010 and ΔRMSEA ≤ -.015.

Table 1. *Studies Reporting Measurement Models of Executive Functions: Sample Characteristics and Study Quality*

Age Group ($\bar{x}$ age)	Author	N	Age (years): $\bar{x}$ (SD)	Age Range (years)	% Female	% White or Category	Education: $\bar{x}$ (years) or Category	Study Quality[*]
Preschool (<6 yrs.)	Carlson et al. (2014)	104	4.00 (0.43)	3-5	46.15	80.00	Some preschool	9
	Lerner & Lonigan (2014)	289	4.65 (0.63)	3-5	53.00	57.00	–	8
	Masten et al. (2012)	138	5.77 (0.58)	4.83-6.92	56.50	4.30	–	6
	Miller et al. (2012)[+]	129	4.17 (0.58)	3-5	39.53	80.00	–	9
	Monette et al. (2015)	272	5.70 (0.34)	–	54.55	–	–	10
	Usai et al. (2014)[+]	175	5.71 (0.28)	5-6	43.43	–	Kindergarteners	9
	Wiebe et al. (2008)	243	3.92 (1.00)	2-6	55.56	70.37	Preschool	9
	Wiebe et al. (2011)	228	3.01 (0.04)	–	49.56	75.88	–	9
	Willoughby et al. (2012a)	1036	5.03 (0.26)	–	50.00	–	–	8
School-Aged (6-12 yrs.)	Agostino et al. (2010)[+]	155	10.08 (1.25)	8-13	56.00	–	21.94% Grade 3; 25.81% Grade 4; 28.39% Grade 5; 23.87% Grade 6	7
	Arán-Filippetti (2013)[1+]	LSES: 124 MSES: 124	–	8-12	–	–	Some grade school	8
	Brocki & Tillman (2014)	114	9.32 (2.31)	5-14	47.00	68.00	–	10
	Brydges et al. (2012)[+]	215	8.33 (1.08)	7-9	48.84	–	–	9
	Duan et al. (2010)[+]	61	11.88 (0.65)	11-12	44.27	From "Chinese schools"	–	7
	Lambek & Shevlin (2011)[2]	164	–	7-12	47.00	–	–	5
	Lee et al. (2012)	163	6.90 (0.31)	–	49.69	"Mainly ethnic Chinese"	–	8
	Lee et al. (2013)[3]	332	–	All 8	–	–	–	9
	Lehto et al. (2003)[+]	103	10.50 (1.30)	8-13	44.44	–	–	8
	Rose et al. (2012): Full-Term[4+]	131	11.14 (0.35)	10.5-12.5	49.30	16.10	–	8
	Rose et al. (2012): Pre-Term[4+]	–	11.18 (0.44)	10.4-12.1	–	11.40	–	
	van der Sluis et al. (2007)	172	10.67 (0.72)	9-12	51.16	–	58.14% - Grade 4; 41.86% - Grade 5	10
	van der Ven et al. (2013)	211	6.42 (0.37)	5-7	47.87	–	–	11
	Xu et al. (2013)[5+]	140	8.78 (0.57)	7-9	47.86	"Chinese"	–	8

		N	M (SD)	Range	%	Race	Education	#
		165	11.59 (0.88)	10-12	49.09	"Chinese"	–	
Adolescents (13-17 yrs.)	Friedman et al. (2011)[+]	813	17.30 (0.60)	15-20	51.66	–	–	11
	Lambek & Shevlin (2011)[2]	75	–	13-16	45.00	–	–	5
	Xu et al. (2013)[5+]	152	14.41 (0.86)	13-15	50.00	"Chinese"	–	8
Adults (18-59 yrs.)	Chuderski et al. (2012)	160	21.90 (2.70)	15-35	61.25	–	–	8
	Fleming et al. (2016)[+]	420	22.50	–	50.00	91.00	–	10
	Fournier-Vicente et al. (2008)	180	23.62 (3.24)	18-31	50.00	–	Undergraduates	11
	Ito et al. (2015)[+]	484	19.75 (2.21)	18-42	49.18	86.16	Undergraduates	11
	Klauer et al. (2010)[6] - Study 1[+]	125	23.10 (5.80)	17-57	42.97	–	–	8
	Klauer et al. (2010)[6] - Study 2[+]	118	23.50 (4.20)	18-42	35.25	–	–	9
	McVay & Kane (2012)	258	–	18-35	–	–	Undergraduates	9
	Miyake et al. (2000)[+]	137	–	–	–	–	Undergraduates	9
	Was (2007)	188	25.70	18-56	70.21	–	Undergraduates	8
Older Adults (>60 yrs.)	Adrover-Roig et al. (2012)	122	62.30 (8.40)	48-91	65.00	"Predominantly Caucasian"	11.30	9
	Bettcher et al. (2016)	202	73.68 (6.60)	63-99	50.50	–	17.67	8
	de Frias et al. (2009): CE group[+]	77	66.05 (7.83)	55-86	67.54[7]	–	15.81	7
	de Frias et al. (2009): CN group[+]	276	68.45 (8.65)	54-88	67.54[7]	–	15.29	
	Frazier et al. (2015)	119	73.00 (6.50)	55-99	54.00	–	17.50	1
	Hedden & Yoon (2006)[+]	121	72.24 (4.28)	63-82	57.02	–	15.69	8
	Hull et al. (2008)[+]	100	60.24 (5.58)	51-74	80.00	–	25%-High School; 2% -Associates; 49% - Bachelor's; 24% - Advanced degree	7
	Vaughan & Giovanello (2010)	95	74.40 (6.40)	60-90	56.00	85.00	16.10	8
Multiple Ages	Huizinga et al. (2006)[8]	71	7.2	6-8	54.93	–	0.56	4
		108	11.2	10-12	57.41	–	3.92	
		111	15.3	14-16	52.25	–	7.2	
		94	20.8	18-26	76.6	–	10.55	
	Pettigrew & Martin (2014)[9]	102	21.00 (3.10)	18-32	–	–	14.00	10

60	71.00 (5.00)	64-87	–	–	16.00

Note. CE = Cognitively Elite; CN = Cognitively Normal; LSES = Low Socioeconomic Status Group; MSES = Medium Socioeconomic Status Group.

[*]Study Quality based on items listed under Data Extraction subheading in the Methods section.

[+]Indicates inclusion in the re-analysis.

[1]Arán-Filippetti (2013) reported confirmatory factor analyses for two separate groups (LSES and MSES).

[2]Lambek & Shevlin (2011) reported two separate confirmatory factor analyses for child and adolescent groups.

[3]Lee et al. (2013) provided a far more comprehensive span of ages; however, due to its sequential cohort-design, there was significant overlap between participants at different ages. In order to ensure that the same individuals were not represented twice in the systematic review, and to increase comparability with other designs, only the cross-section with the greatest amount of participants is considered in the current review and presented in the current table. There is a significant amount of demographic information provided in the original article for the cohorts at baseline; however, the data was not available for the cohort selected for consideration in the current review.

[4]Demographic statistics for Rose et al. (2012) reported separately for full-term and pre-term participants, but only one confirmatory factor analysis was run using the full sample. Some statistics were pulled from Rose et al. (2011), which used the same participant sample.

[5]Xu et al. (2013) reported three separate confirmatory factor analyses for two child and one adolescent group.

[6]Klauer et al. (2010) reported two separate studies, involving separate samples and separate confirmatory factor analyses.

[7]de Frias et al. (2009) did not report separate gender breakdowns for their CE and CN subgroups, so the value reported above was from full sample.

[8]Huizinga et al. (2006) reported demographics for four separate age groups, and reported fit indices corresponding to a configural invariance model across age groups.

[9]Pettigrew & Martin (2014) merged their young and old participants into one group for their confirmatory factor analysis, but did not report separate demographic characteristics for the merged group.

Table 2. *Studies Reporting Measurement Models of Executive Functions: Fit Indices and Latent Constructs*

Age Group	Author	χ^2 (p)	df	CFI	RMSEA	$\hat{\pi}^1$	Accepted Model	EF-related Factors	Factors tested, but removed/merged	Non-EF Factors in Model
Preschool (<6 yrs.)	Carlson et al. (2014)[2]	24.25 (0.15); 24.56 (0.14)	18; 18	0.96; 0.96	0.06; 0.06	0.15	Both One- and Two-Factor Acceptable	EF; Conflict EF, Delay EF	Conflict and Delay EF merged to form EF	None
	Lerner & Lonigan (2014)	55.60*	33	0.97	0.05	0.78	Two-Factor	Inhibitory Control, WM	Inhibitory Control - Suppression and Inhibitory Control - Conflict merged to form Inhibitory Control	None
	Masten et al. (2012)	–	–	0.97	0.04	–	One-Factor	EF	Hot EF and Cool EF merged to form EF	IQ
	Miller et al. (2012)[+]	43.41	42	1.00	0.02	0.39	Two-Factor	Inhibition, WM	WM and Set-Shifting merged to form WM	None
	Monette et al. (2015)	60.92 (0.59)	64	1.00	0.00	0.88	Two-Factor	Inhibition, Flexibility-WM	Flexibility and WM merged to form Flexibility-WM	Speed (Control Factor)
	Usai et al. (2014)[+]	9.48	8	0.98	0.03	0.20	Two-Factor	Inhibition, WM-Shifting	WM and Shifting merged to form WM-Shifting	None
	Wiebe et al. (2008)	31.14 (0.27)	27	0.99	0.03	0.52	One-Factor	EF	WM, Interference from Distractors, and Proactive Interference merged to form EF	None
	Wiebe et al. (2011)	14.84 (0.39)	14	0.99	0.02	0.36	One-Factor	EF	Inhibition and WM and merged to form EF	None
	Willoughby et al. (2012a)	6.30 (0.71)	9	1.00	0.00	0.96	One-Factor	EF	Inhibitory Control/Attention Shifting and WM merged to form EF	None

School-Aged (6-12 yrs.)	Agostino et al. (2010)[+]	33.26 (0.23)	28	0.98	0.035	0.32	Three-Factor	Inhibition, Updating, Shifting	None	Mental-Attentional Capacity
	Arán-Filippetti (2013)[3]: LSES[+]	30.65 (0.13)	23	0.97	0.05	0.18	Three-Factor	Inhibition, WM, Cognitive Flexibility	None	None
	Arán-Filippetti (2013)[3]: MSES[+]	21.35 (0.56)	23	1.00	0.00	0.18	Three-Factor	Inhibition, WM, Cognitive Flexibility	None	None
	Brocki & Tillman (2014)	16.78 (0.61)	19	1.00	<.001	0.15	Two-Factor	Inhibition, WM	None	None
	Brydges et al. (2012)[+]	20.11 (0.45)	20	1.00	0.01	0.33	One-Factor	EF	Inhibition, Shifting and WM merged to form EF	None
	Duan et al. (2010)[4+]	8.04 (0.24)	–	0.98	0.08	–	Three-Factor	Inhibition, Updating, Shifting	None	None
	Lambek & Shevlin (2011)[5]	3.07 (0.80)	6	1.00	0.00	0.10	Three-Factor	Inhibition, Verbal WM, Visuospatial WM	None	None
	Lee et al. (2012)	135.14*	86	0.94	0.06	0.66	Two-factor	Inhibition/Switch, Updating	Inhibition and Switching merged to form Inhibition/Switch	Reaction Time, Flanker Task, Simon Task (All Control Factors)
	Lee et al. (2013)[6]	145.47*	68	0.97	0.06	0.99	Two-Factor	Inhibition/Switch, Updating	Inhibition and Switching merged to form Inhibition/Switch	Control conditions for each task predicted indicators from the same task
	Lehto et al. (2003)[+]	13.73	16	1.00	–	0.13	Three-Factor	Inhibition, WM, Shifting	None	None
	Rose et al. (2012)[+]	41.88 (0.11)	32	0.96	0.05	0.32	Three-Factor	Inhibition, WM, Shifting	WM: Storage and WM: Storage and Processing merged to form WM	None

Group	Study	χ²	df	CFI	RMSEA	SRMR	Model	Factors	Merged	Control
	van der Sluis et al. (2007)	190.99*	122	0.95	0.05	0.78	Nested Factor Model	Updating, Shifting	Inhibition merged with Naming	Naming (Control factor)
	van der Ven et al. (2013)	173.43* (0.00)	121	0.96	0.05	0.93	Two-Factor	Inhibition/Shifting, Updating	Inhibition and Shifting merged to form Inhibition/Shifting	Verbal Speed, Motor Speed (Both Control Factors)
	Xu et al. (2013)[7]: Ages 7-9[+]	15.65 (0.34)	14	0.95	0.03	0.19	One-Factor	EF	Inhibition, Updating WM, and Shifting merged to form EF	None
	Xu et al. (2013)[7]: Ages 10-12[+]	19.24 (0.30)	14	0.95	0.05	0.19	One Factor	EF	Inhibition, Updating WM, and Shifting merged to form EF	None
Adolescents (13-17 yrs.)	Friedman et al. (2011)[+]	53.56*	21	0.96	0.04	0.99	Nested Factor Model	EF, Updating, Shifting	Inhibition merged with EF	None
	Lambek & Shevlin (2011)[5]	3.99 (0.67)	6	1.00	0.00	0.08	Three-Factor	Inhibition, Verbal WM, Visuospatial WM	None	None
	Xu et al. (2013)[7]: Ages 13 to 15[+]	15.72 (0.15)	11	0.95	0.05	0.15	Three-Factor	Inhibition, Updating WM, Shifting	None	None
Adults (18-59 yrs.)	Chuderski et al. (2012)	70.20	60	0.96	0.02	0.52	Four-Factor	Attention Control, Interference Resolution, Response Inhibition, Storage Capacity	Updating merged with Storage Capacity	None
	Fleming et al. (2016)[8+]	30.36 (0.09)	21	0.97	0.03	0.74	Nested Factor Model	EF, Updating, Shifting	Inhibition not tested, but indicators included on EF bifactor	None
	Fournier-Vicente et al. (2008)	91.62 (0.17)	80	0.99	0.03	0.83	Five-Factor	Verbal SPC, Visuospatial SPC, Selective Attention, Shifting, Strategic Retrieval	Dual-Task Coordination removed	None
	Ito et al. (2015)[+]	32.01 (0.04)*	20	0.98	0.04	0.87	Nested Factor Model	EF, Updating, Shifting	Inhibition not tested, but indicators included on EF bifactor	None
	Klauer et al. (2010)[9] - Study 1[+]	12.82 (0.38)	12	0.98	0.02	0.15	Two-Factor	Inhibition/WM, Switching	Inhibition merged with WM to form Inhibition/WM	None

	Klauer et al. (2010)[9] - Study 2[+]	41.09 (0.13)	32	0.94	0.05	0.20	Three-Factor	Inhibition, WM, Switching	None	None
	McVay & Kane (2012)	194.51*	126	0.92	0.05	0.99	Two-Factor	WM Capacity, Attention Control	None	Task-unrelated thoughts, Reading Comprehension
	Miyake et al. (2000)[+]	20.29 (0.65)	24	1.00	–	0.28	Three-Factor	Inhibition, Updating, Shifting	None	None
	Was (2007)	12.61 (0.13)	8	0.97	0.06	0.20	Two-Factor	Inhibiting, Updating	None	None
Older Adults (>60 yrs.)	Adrover-Roig et al. (2012)	19.86 (0.70)	24	1.00	0.00	0.18	Three-Factor	WM, Shifting, Access	Inhibition and Updating merged to form WM	None
	Bettcher et al. (2016)	144.12*	95	0.96	0.05	0.88	Two-Factor	Shifting/Inhibition, Updating/WM	Mental Set-shifting and Inhibition merged to form Shifting/Inhibition	Speed (Control Factor)
	de Frias et al. (2009)[10]: CE Group[+]	6.53 (0.69); 5.55 (0.48)	9; 6	1.00; 0.98	0.00; 0.00	0.11	Three-Factor	Inhibition, Updating, Shifting	None	None
	de Frias et al. (2009)[10]: CN Group[+]	17.11 (0.05); 5.11 (0.53)	9; 6	0.94; 1.00	0.06; 0.00	0.32	Two-factor	Not specified for untested two-factor model	None	None
	Frazier et al. (2015)	–	–	–	–	–	Two-Factor	WM, Cognitive Control	Inhibition merged with Set-Shifting to form Cognitive Control	Processing Speed (Control)
	Hedden & Yoon (2006)[+]	115.09	125	1.00	0.00	0.50	Two-Factor	Shifting/Updating, Resistance to Proactive Interference	Shifting and Updating merged to form Shifting/Updating; Prepotent Response Inhibition merged with Speed	Verbal Memory, Visual Memory, Speed
	Hull et al. (2008)[+]	17.76	14	–	0.05	0.13	Two-Factor	Updating, Shifting	Inhibition removed	None
	Vaughan & Giovanello (2010)	30.23 (0.18)	24	0.97	0.05	0.18	Three-factor	Inhibition, Updating, Task Switching	None	None

| Multiple Ages | Huizinga et al. (2006)[11] | 139.34* | 67 | – | – | – | Two-Factor | Stop-Signal Inhibition, Eriksen Flanker Inhibition, Stroop Inhibition, WM, Shifting | Inhibition split into three single-item factors | Basic Speed (Control) |
| | Pettigrew & Martin (2014)[12] | 55.23 | 42 | 0.95 | 0.04 | .39 | Two-Factor | WM, Interference Resolution | Response-distractor Inhibition and Resistance to Proactive Interference Merged to form Interference Resolution | Age (Control) |

Note. CE = Cognitively Elite; CFI = Comparative Fit Index; CN = Cognitively Normal; EF = Executive Function; LSES = Low Socioeconomic Status Group; MSES = Medium Socioeconomic Status Group; RMSEA = Root Mean Square Error of Approximation; SPC = Storage and Processing Coordination; WM = Working Memory; $\hat{\pi}$ = Estimated Power.

*Indicates a significant χ^2 test of model fit (p<.05). [+]Indicates inclusion in the re-analysis.

[1]Power was estimated based on tables provided by Hancock (2006) for post-hoc power analyses of model fit. The values provided herein were based on tables for models with an RMSEA=.00. Because Hancock provided n or df values in increments of 50 and 5, respectively, the n and df values from the studies included in the systematic review were rounded to the nearest increments. For models that did not report their df, a power value was not estimated, and the studies reporting these models were provided no points for the power criterion of the study quality scale.

[2]Carlson et al. (2014) did not report a preference for either their one- or two-factor model, and the results for both models are reported here, with the one-factor fit indices coming before the semicolon and the two-factor fit indices coming after the semicolon.

[3]Arán-Filippetti (2013) reported confirmatory factor analyses for two separate groups (LSES and MSES).

[4]Duan et al. (2010) reported a χ^2/df value, which is reported here in place of a χ^2 value.

[5]Lambek & Shevlin (2011) reported two separate confirmatory factor analyses for child and adolescent groups.

[6]Lee et al. (2013) used a sequential cohort design, where they recruited participant at different baseline ages and assessed them longitudinally over the course of four years. Consequently, the summary data and fit indices provided for each age group involved a variable amount of overlap (e.g., children starting at age 8 were combined with children that started at age 5 that had already completed three past annual waves of data collection). In turn, only the fit indices from the time point with the largest amount of participants was considered to avoid representing the same individuals twice in the analyses.

[7]Xu et al. (2013) reported three separate confirmatory factor analyses for two child and one adolescent group.

[8]Fleming et al. (2016) and Ito et al. (2015) both included indicators for an inhibition factor, but had these indicators load directly on a general EF bifactor. Guided by previous research, these authors never tested a model including a specific inhibition factor; but because the model included these indicators, inhibition is listed as a factor tested, but removed/merged.

[9]Klauer et al. (2010) reported two separate studies, involving separate samples and separate confirmatory factor analyses.

[10]de Frias et al. (2009) concluded that the data supported a three-factor solution for the CE group (based partially on longitudinal invariance testing); however, the one-factor model fit the data better at Wave 1, and this model was also more parsimonious. The authors concluded a two-factor model best fit the data CN group, although such a model was not tested by the researchers. The fit indices reported herein derive from the one-factor and three-factor models at Wave 1 in their longitudinal design, with the one-factor fit indices coming before the semicolon and the three-factor fit indices coming after the semicolon.

[11]Huizinga et al. (2006) reported fit indices corresponding to a configural invariance model across age groups. Because the sample size was dispersed across the age groups, an estimate of power was not provided for this study.

[12]Pettigrew & Martin (2014) merged their young and old participants into one group for their confirmatory factor analysis.

Table 3. *Counts and Frequencies of Constructs represented in Accepted Measurement Models*

	Age Group (Age range)	k	EF	Inhibition	UWM	Shifting	Inhibition/Shifting	Inhibition/UWM	Shifting/UWM	SR/Access
Counts (*k*)	All Ages	46	11	24	33	20	5	1	3	2
	Preschool (<6 yrs.)	9	5	4	2	0	0	0	2	0
	School-Aged (6-12 yrs.)	15	3	8	12	7	3	0	0	0
	Adolescents (13-17 yrs.)	3	1*	2	3	2	0	0	0	0
	Adults (18-59 yrs.)	9	2*	6	8	6	0	1	0	1
	Older Adults (>60 yrs.)	8	0	3	6	4	2	0	1	1
Frequencies (%)	All Ages	46	23.91	52.17	71.74	43.48	10.87	2.17	6.52	4.35
	Preschool (<6 yrs.)	9	55.56	44.44	22.22	0	0	0	22.22	0
	School-Aged (6-12 yrs.)	15	20.00	53.33	80.00	46.67	20.00	0	0	0
	Adolescents (13-17 yrs.)	3	33.33	66.67	100	66.67	0	0	0	0
	Adults (18-59 yrs.)	9	22.22	66.67	88.89	66.67	0	11.11	0	11.11
	Older Adults (>60 yrs.)	8	0	37.50	75.00	50.00	25.00	0	12.50	12.50

Note. * The EF factor observed for adolescent and adult samples were general bifactors in models that also included updating and shifting in the same model. EF = Executive Function; SR = Strategic Retrieval; UWM = Updating/Working Memory. The names attributed to similar constructs differed across studies. Selective Attention, Attention Control, Interference Resolution and Response Inhibition, Resistance to Proactive Interference, Inhibitory Control, Inhibiting, and Interference Resolution were subsumed under Inhibition. Updating, WM, WM Capacity, and Storage Capacity were subsumed under Updating/Working Memory. Cognitive Flexibility, Flexibility, Task Switching, and Switching were subsumed by Shifting. Cognitive Control was subsumed under Inhibition/Shifting. Strategic Retrieval and Access were subsumed under Strategic Retrieval/Access. Based on semantic overlap (Packwood et al., 2011), Selective Attention (Fournier-Vicente et al., 2008) and Attention Control (Chuderski et al., 2012) could be subsumed under Shifting; however, the indicators for these factors from both studies were more closely related to Inhibition (e.g., Stroop, Antisaccade), and were thus subsumed under that construct.

Some studies found multiple factors interpretable as sub-dimensions of a common EF-related construct. In these cases, these multiple factors were tallied as representative of a single factor. Specifically, Lambek and Shevlin (2011) found separable Verbal and Visuospatial WM factors, which were tallied as one observation of an Updating/WM factor for each of these authors' two reported samples. Chuderski et al. (2012) found separable Attention Control, Interference Resolution and Response Inhibition factors, which were tallied as one observation of an inhibition factor based on their similarities to this construct based on the authors' conceptual and operational definitions. Lastly, Fournier-Vicente et al. (2008) found separable Verbal and Visuospatial Storage and Processing Coordination, which were tallied as one observation of Updating/WM.

Carlson et al. (2014) did not report a preference for either their one-factor or two-factor model. Based on fit indices, the one-factor was more parsimonious and showed nearly identical fit to the two-factor model. In turn, an EF factor was added to the tally for this study. For the Cognitively Normal group described by de Frias et al. (2009), the authors reported an untested two-factor model as their accepted model. Because this model was untested, it is not clear which factors were represented in this two-factor model, and the results of this group are not represented within this table.

Supplementary Materials #1: Bootstrapping Method Validation, Supplementary Tables, and

Excluded Article List

The Unity and Diversity of Executive Functions: A Systematic Review and Re-Analysis of

Latent Variable Studies

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Bootstrapping Method Validation

The bootstrap method followed a specific sequence based on the observed correlation martix and sample size reported by each study. This method is outlined below.

1) Given the reported correlation matrix Σ and sample size n

    a. Do: For bootstrapped samples $i = (1, 2, \ldots, K)$

        i. Draw n sample from $N(0, \Sigma)$

        ii. Compute observed correlation matrix $\hat{\Sigma}_i$

        iii. Do: For each model

            1. Fit factor model to $\hat{\Sigma}_i$

            2. Compute fit indices and factor correlations

2) Compute summary statistics for each model

In terms of validating the approach, the correlation matrices for the 16-69 year-old sample from the Wechsler Adult Intelligence Scale, Fourth Edition (WAIS-IV; $N = 1,800$; Wechsler, 2008) and the 6-16 year-old sample from the Wechsler Intelligence Scale for Children, Fifth Edition (WISC-V; $N = 2,200$; Wechsler, 2014) were re-analyzed using the bootstrapping method. The WAIS-IV and WISC-V models were based on confirmatory factor analyses conducted using large, nationally stratified normative samples. The four-factor measurement model for the WAIS-IV has been replicated in a re-analysis (Weiss, Keith, Zhu, & Chen, 2013a) and the newly introduced five-factor model for the WISC-V has been previously postulated with older versions of the test battery (Weiss, Keith, Zhu, & Chen, 2013b). Although these models are not without controversy (Canivez & Kush, 2013), testing these models using the bootstrapping approach would determine whether a frequently evaluated and replicated model consistently produces model fit indices within an acceptable range.

The models specified for these correlation matrices were those reported for all primary and secondary subtests as the best fitting models in the technical manuals for each test. For the WAIS-IV, the model was a second-order factor model with four first-order factors (i.e., Verbal Comprehension, Perceptual Reasoning, Working Memory, and Processing Speed) and 15 manifest variables, with a co-loading of Arithmetic on Verbal Comprehension and Working Memory and a co-loading of Figure Weights on Perceptual Reasoning and Working Memory. The errors for Digit Span and Letter-Number Sequencing were also allowed to correlate in this model. For the WISC-V, the model was a second-order factor model with five first-order factors (i.e., Verbal Comprehension, Visual Spatial, Fluid Reasoning, Working Memory, Processing Speed) and 16 manifest variables, including a constrained loading of 1.0 from Fluid Reasoning onto the second-order factor and a three-way co-loading of Arithmetic onto three first-order factors: Verbal Comprehension, Fluid Reasoning, and Working Memory.

The bootstrapping re-analysis of the WAIS-IV correlation found that the accepted model for the WAIS-IV converged for 100% of the bootstrapped samples, with 100% of samples meeting lenient fit thresholds (i.e., CFI $\geq$.90, RMSEA $\leq$.08). In terms of the strict fit thresholds, 99.76% of bootstrapped samples had a CFI $\geq$.95, but 0% had an RMSEA $\leq$.05. The mean CFI (95% CI) was 0.96 (0.95, 0.97) and the mean RMSEA was 0.06 (0.059, 0.07). The estimated power for this model ($df = 79$) was 0.99. Using the WISC-V correlation matrix, the accepted model for the WISC-V converged for 100% of samples, with 100% of these samples meeting the lenient fit thresholds. The strict fit threshold of CFI $\geq$.95 was met for 94.04% of bootstrapped sample, while 0% of samples met the strict RMSEA $\leq$.05 threshold. For the WISC-V, the mean RMSEA was 0.06 (0.053, 0.06) and the mean CFI was 0.95 (0.948, 0.96). The estimated power for this model ($df = 92$) was also 0.99.

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Table S1. *Child/Adolescent Studies: Tests used as Indicators for Executive Function Factors in Accepted Measurement Models*

Author[1]	Inhibition	UWM	Shifting	Inhibition/Shifting
Agostino et al. (2010)	Antisaccade Task	Letter Memory Task	Contingency Naming Task	
	Stroop: Number version	Visual N-Back Task: 0- back, 1- back, 2-back	Trail Making Test	
	Stroop: Color version			
Arán-Filippetti et al. (2013)	Matching Familiar Figures Test	WISC-IV Letter-Number Sequencing	Semantic Verbal Fluency Test	
	Porteus Maze Test	WISC-IV Digit Span Forward	Phonological Verbal Fluency	
	Stroop Color-Word Test	WISC-IV Digit Span Backward	Wisconsin Card Sorting Test: Categories Completed	
Brocki et al. (2014)	Stroop Color-Word Test	Box Task		
	Day-Night Stroop-like Task	WISC-III Digit Span Backward		
	Attention Network Task: Child version	Letter-Number Sequencing		
	Go/No-go Task	Pig House task		
Brydges et al. (2012)	Stroop task: Color-Word	WISC-IV Letter-Number Sequencing	Wisconsin Card Sorting Test: Perseverative Errors	
	Go/No-go Task	WISC-IV Digit Span Backward	Verbal Fluency	
	Compatibility Reaction Time	NEPSY Sentence Repetition	Letter Monitoring	
Duan et al. (2010)	Digit Go/No-go Task	Digit 2-back Task	Odd-More Task: Digit Shifting Task	
	Figure Go/No-go Task	Figure Position 2-back	Local Global: Figure Shifting Task	
Huizinga et al. (2006)[2]	Stop-Signal Task	Tic Tac Toe Task	Local Global Task	
	Eriksen Flanker Task	Mental Counters Task	Dots Triangles Task	
	Stroop Task	Running Memory	Smiling Faces Task	
Lambek & Shevlin (2011)[3]	Stop Task	Digit Span Backward		
	Walk Don't Walk	Letters Backward		
		WISC-III-PI Spatial Span Backward		
		Finger Windows Backward		

Author[1]	Inhibition	UWM	Shifting	Inhibition/Shifting
Lee et al. (2012)	Flanker Task (RT): Incongruent Condition	Mister X Task	Flanker Task (RT): Switch Condition	
	Simon task (RT): Incongruent Condition	Listening Recall Task	Simon task (RT): Switch Condition	
	Flanker task (Accuracy): Incongruent Condition	Pictorial Updating Task	Picture-Symbol Task (RT): Switch Condition	
	Simon task (Accuracy): Incongruent Condition	Flanker task: Accuracy, Switch Condition	Simon Task (Accuracy): Switch Condition	
			Picture-Symbol task (Accuracy): Switch Condition	
Lee et al. (2013)	Flanker Task: Incongruent Condition	Listening Recall Task	Flanker Task: Switch Condition	
	Simon Task: Incongruent Condition	Mister X Task	Simon Task: Switch Condition	
	Mickey Task: Incongruent Condition	Pictorial Updating Task	Picture-Symbol Task: Switch Condition	
Lehto et al. (2003)	CANTAB Tower of London	NEPSY Auditory Attention and Response Set B	NEPSY Word Fluency Task	
	Matching Familiar Figures Test	CANTAB Spatial Span Task	Trail Making Test B	
		CANTAB Spatial Working Memory Task		
		WISC-R Mazes Task		
Lerner & Lonigan (2014)[4]	Bird and Dragon Task	Word Span Reversed Task		
	Luria's Hand Game Task	Listening Span Task		
	Picture Imitation	Size Ordering Task		
	Block Sorting	Object Span Task		
	Day-Night Stroop			
	Knock-Tap Task			
Miller et al. (2012)	Preschool Continuous Performance Test: Commission Errors and Ratio	Backward Digit Span	Dimensional Change Card Sort: Border Version;	
	Boy-Girl Stroop	Backward Word Span Test	Go/No-Go 2: Hit Ratio	
	Tower of Hanoi	Boxes Task: Hit Ratio	Go/No-Go 3: Hit Ratio	
	Go/No-Go: Commission Errors and Ratio	Preschool Continuous Performance Test: Omissions		

Author[1]	Inhibition	UWM	Shifting	Inhibition/Shifting
Monette et al. (2015)	Fruit Stroop Task Interference: Correct Responses Hand Stroop Interference: Correct Responses Day-night Test: Correct Responses Fruit Stroop Interference: Errors Hand Stroop Interference: Errors Day-Night Test: Errors	Backward Word Span: Correct Responses Backward Block Span: Correct Responses Trails-P Test: Perseverative Errors Face Sort: Perseverative Errors	Verbal Fluidity Shift: Shift Errors Card Sort: Perseverative Errors	
Rose et al. (2012)[5]	Go/No-go CANTAB Rapid Visual Information Processing	CANTAB Spatial Span Pattern Span Change Detection CANTAB Spatial Working Memory Counting Span Listening Span	Trail-Making: Time B - A CANTAB Intradimensional-Extradimensional Shift: Reversal Trials	
Usai et al. (2014)	Circle Drawing Task Tower of London Task	Dual Request Selective Task Backward Digit Span	Semantic Fluency Dimensional Change Card Sort	
van der Sluis et al. (2007)	Numerical Size Inhibition Object Inhibition Task Stroop Color-Word Test Quantity Inhibition Task	Letter Memory Task Digit Memory Task Keep Track Task	Making Trails Task Objects Shifting Task Place Shifting Task Symbol Shifting Task	
van der Ven (2013)	Animal Stroop Task: Inhibition Accuracy Local Global Task: Inhibition Accuracy Simon Task: Inhibition Accuracy Animal Stroop: Inhibition Speed Local Global: Inhibition Speed Simon Task: Inhibition Speed	Digit Span Backwards Task Odd One Out Task Keep Track Task	Animal Shifting Task: Shifting Accuracy Sorting Task: Shifting Accuracy Animal Shifting: Shifting Speed Sorting Task: Shifting Speed Trail Making Test in Colors: Shifting Accuracy Trail Making Test in Colors: Shifting Speed	

Author[1]	Inhibition	UWM	Shifting	Inhibition/Shifting
Wiebe et al. (2008)[6]	Child Continuous Performance Test	Six Boxes Test		
	NEPSY Statue Subtest	Delayed Alternation Task		
	Tower of Hanoi Task	Digit Span Subtest: Differential Abilities Scale		
	NEPSY Visual Attention Subtest			
	Delayed Response Task			
	Shape School Inhibit Condition			
	Whisper Task			
Wiebe et al. (2011)	Big-Little Stroop Task	Nebraska Barnyard Task		
	Go/No-go Task	Nine Boxes Task		
	Shape School Task: Inhibit Condition	Delayed Alternation Task		
	Snack Delay Task			
Willoughby et al. (2012a)		Working Memory Span		Simon Task: Spatial Conflict Arrows:
		Pick the Picture		Animal Go No-Go Task
				Silly Sounds Stroop Task
				Something's the Same Task
Xu et al. (2013)	Go/No-go	N-back Task: 1-back, 2-back	Number-Pinyin Task	
	Color-Word Stroop Task: RT Ratio	Running Memory Task	Dots-Triangles Task	

Note. CANTAB = Cambridge Neuropsychological Test Automated Battery; EF = Executive Function; RT = Reaction Time; UWM = Updating/Working Memory. WISC = Wechsler Intelligence Scale for Children. The constructs of Updating and Working Memory were subsumed under the column UWM. The constructs of Set-Shifting, Flexibility, Cognitive Flexibility, and Switching were subsumed under the column of Shifting. The construct of Inhibitory Control/Attention Shifting, represented by just Willoughby et al. (2012a) was subsumed under Inhibition/Shifting.

[1]Two studies assigned tests to constructs not represented in the table above. Carlson et al. (2014) assigned Bear/Dragon, Backward Digit Span, Less is More, Grass/Snow, and the Dimensional Change Card Sort to Conflict EF; and Gift Delay, Delay of Gratification, and Tower Building to Delay EF. Masten et al. (2012) assigned Dinky Toys, Gift Delay Part I, and Gift Delay Part II to Hot EF; and Simon Says, Dimensional Change Card Sort, Computerized Pointing Stroop, and Peg Tapping to Cool EF.

[2]Huizinga et al. (2006) had multiple age groups, ranging from 6 to 26, but because the age groups were predominantly child/adolescent, they were included in this table.

[3]Lambek and Shevlin (2011) assigned indicators to both Verbal and Visuospatial Working Memory, and the indicators for both constructs listed under the Inhibition category.

[4]Lerner and Lonigan (2014) assigned indicators to Inhibitory Control – Suppression and Inhibitory Control – Conflict, and the indicators for both constructs were listed under the Inhibition category.

[5]Rose et al. (2012) assigned indicators to Working Memory: Storage and Working Memory: Storage and Processing, and the indicators for both constructs were listed under the UWM category.

[6]Wiebe et al. (2008) assigned indicators to Interference from Distractors and Proactive Interference, and the indicators for both constructs were listed under the Inhibition category.

Table S2. *Adult Studies: Tests used as Indicators for Executive Function Factors in Accepted Measurement Models*

Author	Inhibition	UWM	Shifting	Access/SR
Adrover-Roig et al. (2012)		WAIS-III Digit Forward Subtest	Brixton Test: Errors	Boston Naming Test
		CANTAB Paired Associated Learning: Errors	Madrid Card Sorting Test: Switch Cost	Controlled Oral Word Association Test: FAS
		Stroop Test: Color-Word	Madrid Card Sorting Test: Efficient Series	Semantic Fluency: Animals
Bettcher et al. (2016)	Enclosed Flanker Test: Incongruent Condition	Dot Counting: Total Correct	Set-Shifting Task: Shift Trials	
	Antisaccade Task: Proportion Correct	Running-Letter Memory Task: Proportion Correct	Number-letter Task: Shift Trials	
	Stroop Interference Test: Total Correct	N-Back: 1-Back and 2-Back: D-prime	Design Fluency Task: Shift Condition Accuracy	
		Digit Span Backward: Total Span		
Chuderski et al. (2012)[1]	Figure-Word Task: Latency	Keep-Track Task		
	Color-word Task: Latency	N-Back Task: 2-back: Figural		
	Stop-Signal Task	Two-Array Comparison Task		
	Go/No-go Task	Monitoring Task: Verbal Version		
	Figure-Word Task: Accuracy	Monitoring Task: Figural Version		
	Color-word Task: Accuracy			
	Number Stroop Task: Accuracy			
	Antisaccade Task			
de Frias et al. (2009)	Hayling Sentence Completion Test	Reading Span Task	Brixton Spatial Anticipation Test	
	Stroop Test	Computational Span Task	Color Trails Test	
Fleming et al. (2016)	Antisaccade Task	Keep Track Task	Color-Shape Task	
	Stop Signal Task	Letter Memory Task	Category Switch Task	
	Stroop Color-Naming Task	Spatial 2-Back Task	Number-Letter Task	

Author	Inhibition	UWM	Shifting	Access/SR
Freidman et al. (2011)	Antisaccade Task	Keep Track Task	Number-Letter Task	
	Stop-Signal Task	Letter Memory Task	Color-Shape Task	
	Stroop Task	Spatial 2-Back Task	Category-Switch Task	
Fournier-Vicente et al. (2008)[2]	Stroop-Color Test	Backward Digit Span Task	Plus-minus Task	Random Letter Generation Task
	Stroop-Numerical Test	Verbal Transposed Span Task	Number-Letter Task	Hayling Test
	d2 Target Detection Task	Verbal Arithmetic Span Task	Local-Global Task	Semantic Verbal Fluency Task
		Backward Location Span Task		
		Visuospatial Transposed Span Task		
		Visuospatial Arithmetic Span Task		
Frazier et al. (2015)	Stroop Task	Digit Span Backward Task	Design Fluency Switching Test	
	Enclosed Flanker Task	N-Back: 1-back and 2-back	Number-letter Task	
		Dot Counting Task		
		Running-Letter Memory Task		
Hedden & Yoon (2006)[3]	Antisaccade	Letter Memory Task	Plus-Minus Task	
	Stroop Color Naming	Backward Digit Span Task	Wisconsin Card Sorting Task	
	Excluded Letter Fluency 1	Self-Ordered Pointing	Trail Making Test	
	Excluded Letter Fluency 2			
	Semantic Fluency			
Hull et al. (2008)	Stroop Verbal Task	Keep Track Verbal Task	Local-Global Verbal Task	
	Stroop Nonverbal Task	Keep Track Non-Verbal Task	Local-Global Non-Verbal Task	
	Antisaccade Task	N-Back Verbal Task	Plus-Minus Task	
		N-Back Non-verbal Task		
Ito et al. (2015)	Antisaccade Task	Keep Track	Number-Letter	
	Stop-Signal Task	Letter Memory	Color-Shape	
	Stroop Task	Spatial N-back	Category Switch	

Author	Inhibition	UWM	Shifting	Access/SR
Klauer et al. (2010) – Study 1	Stop-Signal Task	Reading Span Task	Color-Size Task	
	Antisaccade Task	Operation Span Task	Number-Letter Task	
			Plus-Minus Task	
Klauer et al. (2010) – Study 2	Flanker Task	Reading Span Task	Color-Size Task	
	Stroop Task	Operation Span Task	Semantic Switching Task	
	Simon Task	Counting Span Task	Number-Letter Task	
	Antisaccade Task			
McVay & Kane (2012)	Numerical Stroop	Operation Span		
	Semantic SART	Reading Span		
	Antisaccade Task	Spatial Span		
Miyake et al. (2000)	Antisaccade Task	Keep Track Task	Plus-Minus Task	
	Stop-signal Task	Tone Monitoring Task	Number-letter Task	
	Stroop Task	Letter Memory Task	Local-global Task	
Pettigrew et al. (2014)[4]	Recent Negatives Task	Automated Operation Span		
	Cued Recall Task	WAIS-R Backwards Digit Span		
	Release from Proactive Interference Task	Sternberg Recognition Task		
	Flanker Task			
	Picture-Word Interference task			
	Non-verbal Stroop Task			
	Stroop Task			
Vaughan & Giovanello (2010)	Stroop Task: RT Correct Incongruent	N-back Task: 1-back, 2-back, and 3-back: Percent Correct	More-Less and Odd-even Task: RT Correct Switch	
	Anticue Task: RT Correct Invalidly Cued	Letter-memory Task: Percent Correct	Number-Letter Task: RT Correct Switch	
	Stop-Signal Task: % Correct	Refreshing Paradigm: Percent Correct	Local-Global Task: RT Correct Switch	
Was (2007)	Number Disengagement Task	Alphabet Working Memory Task		

Author	Inhibition	UWM	Shifting	Access/SR
	Original Stroop Color Task	ABCD Working Memory		
	Number Stroop Task	Numerical Strings Audio Working Memory		

Note. CANTAB = Cambridge Neuropsychological Test Automated Battery; RT = Reaction Time; SART = Sustained Attention to Response Task; SR = Strategic Retrieval; UWM = Updating/Working Memory; WAIS = Wechsler Adult Intelligence Scale. Updating, Working Memory, Storage Capacity, Verbal Storage and Processing Coordination, and Visual Storage and Processing Coordination were subsumed under UWM.

Attention Control, Inhibiting, Interference Resolution, Response Inhibition, Response-distractor Inhibition, Resistance to Proactive Interference, and Selective Attention were subsumed under Inhibition. Task Switching, Switching, Mental Set-Shifting, and Set-Shifting were subsumed under Shifting.

[1]Chuderski et al. (2012) included five factors. Presented in the Inhibition column are the indicators for the Interference Resolution, Response Inhibition, and Attention Control factors. Presented in the UWM column are the indicators for the Updating and Storage Capacity factors.

[2]Fournier-Vicente et al. (2008) included six factors. Presented in the Inhibition column are the indicators for Selective Attention. Presented in the UWM column are the indicators for Verbal Storage and Processing Coordination and Visual Storage and Processing Coordination. Their sixth factor was Dual-Task Coordination, which is not presented in this table. The indicators for this factor included Digit Span + Box-Crossing, Location Span + Categorization, Dual-Storage, and Dual-Processing.

[3]Hedden and Yoon (2006) had two inhibition-related factors (i.e., Prepotent Response Inhibition, Resistance to Proactive Interference), with the indicators for these factors both presented in the Inhibition column.

[4]Pettigrew et al. (2014) included two inhibition-related factors (i.e., Response-distractor Inhibition, Resistance to Proactive Interference), with the indicators for these factors both presented in the Inhibition column.

Table S3. *Child/Adolescent Studies: Percent Convergence, Percent Meeting Fit Criteria, and Rate of Model Acceptance for 5,000 Bootstrapped Samples by Measurement Model and Study*

| Model | Study | % Converged | Percent of Converged Models Meeting Fit Criteria | | | | Rate of Model Acceptance based on Fit Thresholds | | | |
| | | | CFI | | RMSEA | | CFI | | RMSEA | |
			≥.90	≥.95	≤.08	≤.05	≥.90	≥.95	≤.08	≤.05
Bifactor	Agostino et al. (2010)	78%	94%	62%	52%	21%	73%	48%	41%	16%
	Arán-Filippetti (2013)	34%	100%	100%	90%	34%	34%	34%	31%	12%
	Brydges et al. (2012)	3%	88%	50%	80%	34%	3%	2%	2%	1%
	Duan et al. (2010)	52%	23%	4%	1%	1%	12%	2%	1%	1%
	Lehto et al. (2003)	67%	60%	26%	39%	14%	40%	17%	26%	9%
	Miller et al. (2012)	9%	49%	5%	18%	0%	4%	0%	2%	0%
	Rose et al. (2012)	49%	28%	5%	31%	3%	14%	2%	15%	1%
	Usai et al. (2014)	82%	45%	20%	35%	14%	37%	16%	29%	11%
	Xu et al. (2013) - Ages 7-9	44%	83%	59%	76%	48%	37%	26%	33%	21%
	Xu et al. (2013) - Ages 10-12	32%	71%	42%	68%	33%	23%	13%	22%	11%
	Xu et al. (2013) - Ages 13-15	74%	25%	6%	13%	3%	19%	4%	10%	2%
	Median*	49%	71%	42%	52%	21%	23%	13%	22%	9%
	Mean*	48%	64%	39%	50%	21%	28%	16%	20%	8%
Nested Factor	Agostino et al. (2010)	100%	55%	14%	17%	3%	55%	14%	17%	3%
	Arán-Filippetti (2013)	73%	100%	99%	66%	10%	73%	72%	48%	7%
	Brydges et al. (2012)	8%	81%	42%	87%	35%	6%	3%	7%	3%
	Duan et al. (2010)	56%	12%	2%	1%	0%	7%	1%	1%	0%
	Lehto et al. (2003)	77%	45%	17%	29%	9%	35%	13%	22%	7%
	Miller et al. (2012)	14%	3%	0%	1%	0%	0%	0%	0%	0%
	Rose et al. (2012)	60%	25%	4%	30%	3%	15%	2%	18%	2%
	Usai et al. (2014)	94%	21%	8%	21%	6%	20%	8%	20%	6%
	Xu et al. (2013) - Ages 7-9	46%	83%	59%	80%	51%	38%	27%	37%	23%
	Xu et al. (2013) - Ages 10-12	34%	75%	46%	76%	39%	26%	16%	26%	13%
	Xu et al. (2013) - Ages 13-15	76%	29%	8%	19%	5%	22%	6%	14%	4%
	Median*	60%	55%	17%	30%	9%	26%	13%	18%	4%
	Mean*	59%	56%	32%	45%	17%	31%	17%	21%	7%
Three-Factor	Agostino et al. (2010)	34%	94%	65%	65%	30%	32%	22%	22%	10%
	Arán-Filippetti (2013)	65%	92%	7%	0%	0%	60%	5%	0%	0%
	Brydges et al. (2012)	2%	77%	25%	93%	23%	2%	1%	2%	0%
	Duan et al. (2010)	21%	28%	7%	1%	0%	6%	1%	0%	0%
	Lehto et al. (2003)	86%	64%	32%	52%	22%	55%	28%	45%	19%

Model	Study	% Converged	Percent of Converged Models Meeting Fit Criteria				Rate of Model Acceptance based on Fit Thresholds			
			CFI		RMSEA		CFI		RMSEA	
			≥.90	≥.95	≤.08	≤.05	≥.90	≥.95	≤.08	≤.05
	Miller et al. (2012)	86%	4%	0%	2%	0%	3%	0%	2%	0%
	Rose et al. (2012)	60%	2%	0%	5%	0%	1%	0%	3%	0%
	Usai et al. (2014)	24%	56%	30%	45%	19%	13%	7%	11%	5%
	Xu et al. (2013) - Ages 7-9	15%	64%	38%	66%	33%	10%	6%	10%	5%
	Xu et al. (2013) - Ages 10-12	14%	72%	42%	77%	40%	10%	6%	11%	6%
	Xu et al. (2013) - Ages 13-15	26%	37%	13%	32%	10%	10%	3%	8%	3%
	Median*	26%	64%	25%	52%	22%	10%	5%	8%	3%
	Mean*	36%	59%	25%	43%	18%	21%	8%	11%	5%
Inhibition-Shifting Merged	Agostino et al. (2010)	47%	58%	16%	23%	4%	27%	8%	11%	2%
	Arán-Filippetti (2013)	100%	83%	3%	0%	0%	83%	3%	0%	0%
	Brydges et al. (2012)	89%	55%	14%	79%	15%	49%	12%	70%	13%
	Duan et al. (2010)	33%	11%	2%	1%	0%	4%	1%	0%	0%
	Lehto et al. (2003)	98%	41%	16%	38%	12%	40%	16%	37%	12%
	Miller et al. (2012)	88%	0%	0%	0%	0%	0%	0%	0%	0%
	Rose et al. (2012)	92%	0%	0%	2%	0%	0%	0%	2%	0%
	Usai et al. (2014)	35%	24%	10%	28%	9%	8%	4%	10%	3%
	Xu et al. (2013) - Ages 7-9	58%	56%	33%	67%	32%	32%	19%	39%	19%
	Xu et al. (2013) - Ages 10-12	69%	64%	35%	76%	38%	44%	24%	52%	26%
	Xu et al. (2013) - Ages 13-15	98%	28%	8%	31%	6%	27%	8%	30%	6%
	Median*	89%	55%	14%	31%	6%	32%	8%	30%	6%
	Mean*	76%	44%	14%	35%	12%	34%	10%	27%	9%
Inhibition-Updating Merged	Agostino et al. (2010)	59%	58%	16%	23%	4%	34%	9%	14%	2%
	Arán-Filippetti (2013)	64%	74%	1%	0%	0%	47%	1%	0%	0%
	Brydges et al. (2012)	6%	61%	16%	80%	16%	4%	1%	5%	1%
	Duan et al. (2010)	35%	4%	1%	0%	0%	1%	0%	0%	0%
	Lehto et al. (2003)	94%	36%	12%	33%	9%	34%	11%	31%	8%
	Miller et al. (2012)	93%	0%	0%	0%	0%	0%	0%	0%	0%
	Rose et al. (2012)	87%	1%	0%	4%	0%	1%	0%	3%	0%
	Usai et al. (2014)	52%	26%	11%	29%	10%	14%	6%	15%	5%
	Xu et al. (2013) - Ages 7-9	35%	57%	32%	66%	32%	20%	11%	23%	11%
	Xu et al. (2013) - Ages 10-12	40%	63%	37%	76%	39%	25%	15%	30%	16%
	Xu et al. (2013) - Ages 13-15	78%	13%	3%	16%	2%	10%	2%	12%	2%
	Median*	59%	57%	12%	23%	4%	20%	2%	12%	2%
	Mean*	55%	41%	13%	33%	11%	20%	6%	13%	4%

Model	Study	% Converged	Percent of Converged Models Meeting Fit Criteria				Rate of Model Acceptance based on Fit Thresholds			
			CFI		RMSEA		CFI		RMSEA	
			≥.90	≥.95	≤.08	≤.05	≥.90	≥.95	≤.08	≤.05
Shifting-Updating Merged	Agostino et al. (2010)	99%	93%	61%	69%	30%	92%	60%	68%	30%
	Arán-Filippetti (2013)	100%	88%	4%	0%	0%	88%	4%	0%	0%
	Brydges et al. (2012)	54%	50%	12%	75%	12%	27%	6%	41%	6%
	Duan et al. (2010)	44%	5%	0%	0%	0%	2%	0%	0%	0%
	Lehto et al. (2003)	97%	37%	13%	33%	9%	36%	13%	32%	9%
	Miller et al. (2012)	98%	1%	0%	1%	0%	1%	0%	1%	0%
	Rose et al. (2012)	90%	0%	0%	2%	0%	0%	0%	2%	0%
	Usai et al. (2014)	75%	50%	25%	52%	22%	38%	19%	39%	17%
	Xu et al. (2013) - Ages 7-9	56%	57%	31%	65%	31%	32%	17%	36%	17%
	Xu et al. (2013) - Ages 10-12	51%	61%	33%	75%	35%	31%	17%	38%	18%
	Xu et al. (2013) - Ages 13-15	51%	12%	3%	14%	2%	6%	2%	7%	1%
	Median*	56%	50%	12%	33%	9%	31%	6%	32%	6%
	Mean*	71%	45%	17%	37%	13%	35%	13%	25%	9%
Unidimensional	Agostino et al. (2010)	100%	57%	16%	27%	5%	57%	16%	27%	5%
	Arán-Filippetti (2013)	100%	71%	1%	0%	0%	71%	1%	0%	0%
	Brydges et al. (2012)	100%	48%	11%	77%	14%	48%	11%	77%	14%
	Duan et al. (2010)	74%	2%	0%	0%	0%	1%	0%	0%	0%
	Lehto et al. (2003)	100%	21%	6%	21%	5%	21%	6%	21%	5%
	Miller et al. (2012)	99%	0%	0%	0%	0%	0%	0%	0%	0%
	Rose et al. (2012)	100%	0%	0%	1%	0%	0%	0%	1%	0%
	Usai et al. (2014)	95%	24%	10%	34%	10%	23%	10%	32%	10%
	Xu et al. (2013) - Ages 7-9	100%	55%	31%	67%	32%	55%	31%	67%	32%
	Xu et al. (2013) - Ages 10-12	100%	60%	33%	77%	37%	60%	33%	77%	37%
	Xu et al. (2013) - Ages 13-15	100%	12%	3%	17%	2%	12%	3%	17%	2%
	Median*	100%	48%	6%	21%	5%	48%	6%	21%	5%
	Mean*	97%	36%	11%	32%	11%	36%	11%	32%	11%

Note. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation.
*Median and Mean values exclude the two preschool articles listed in the table (Miller et al., 2012; Usai et al., 2014).

Table S4. *Adult Studies: Percent Convergence, Percent Meeting Fit Criteria, and Rate of Model Acceptance for 5,000 Bootstrapped Samples by Measurement Model and Study*

| Model | Study | % Converged | Percent of Bootstrapped Samples Meeting Fit Thresholds | | | | Rate of Model Acceptance based on Fit Thresholds | | | |
| | | | CFI | | RMSEA | | CFI | | RMSEA | |
			≥.90	≥.95	≤.08	≤.05	≥.90	≥.95	≤.08	≤.05
Bifactor	de Frias et al. (2009) - CE	68%	52%	35%	42%	28%	35%	24%	29%	19%
	de Frias et al. (2009) - CN	98%	90%	59%	79%	39%	88%	58%	77%	38%
	Fleming et al. (2016)	8%	95%	46%	98%	39%	8%	4%	8%	3%
	Friedman et al. (2011)	12%	100%	89%	100%	45%	12%	11%	12%	5%
	Hedden & Yoon (2006)	5%	38%	15%	35%	13%	2%	1%	2%	1%
	Hull et al. (2008)	6%	0%	0%	0%	0%	0%	0%	0%	0%
	Ito et al. (2015)	6%	99%	59%	96%	26%	6%	4%	6%	2%
	Klauer et al. (2010) - Study 1	21%	42%	21%	51%	23%	9%	4%	11%	5%
	Klauer et al. (2010) - Study 2	5%	54%	14%	45%	9%	3%	1%	2%	0%
	Miyake et al. (2000)	13%	55%	24%	68%	24%	7%	3%	9%	3%
	Median	10%	55%	30%	60%	25%	8%	4%	9%	3%
	Mean	24%	63%	36%	61%	25%	17%	11%	16%	8%
Nested Factor	de Frias et al. (2009) - CE	71%	56%	39%	49%	32%	40%	28%	35%	23%
	de Frias et al. (2009) - CN	98%	92%	64%	88%	51%	90%	63%	86%	50%
	Fleming et al. (2016)	89%	81%	22%	97%	27%	72%	20%	86%	24%
	Friedman et al. (2011)	96%	100%	37%	99%	10%	96%	36%	95%	10%
	Hedden & Yoon (2006)	5%	35%	12%	41%	11%	2%	1%	2%	1%
	Hull et al. (2008)	25%	0%	0%	0%	0%	0%	0%	0%	0%
	Ito et al. (2015)	96%	87%	14%	86%	6%	84%	13%	83%	6%
	Klauer et al. (2010) - Study 1	22%	47%	27%	59%	28%	10%	6%	13%	6%
	Klauer et al. (2010) - Study 2	34%	10%	1%	15%	0%	3%	0%	5%	0%
	Miyake et al. (2000)	34%	33%	13%	57%	16%	11%	4%	19%	5%
	Median	53%	52%	18%	58%	14%	26%	10%	27%	6%
	Mean	57%	54%	23%	59%	18%	41%	17%	42%	13%
Three-Factor	de Frias et al. (2009) - CE	7%	69%	48%	56%	39%	5%	3%	4%	3%
	de Frias et al. (2009) - CN	37%	93%	68%	84%	49%	34%	25%	31%	18%
	Fleming et al. (2016)	94%	56%	7%	95%	16%	53%	7%	89%	15%
	Friedman et al. (2011)	80%	100%	35%	100%	18%	80%	28%	80%	14%
	Hedden & Yoon (2006)	29%	15%	3%	25%	4%	4%	1%	7%	1%
	Hull et al. (2008)	17%	0%	0%	0%	0%	0%	0%	0%	0%
	Ito et al. (2015)	52%	83%	11%	93%	7%	43%	6%	48%	4%

Model	Study	% Converged	Percent of Bootstrapped Samples Meeting Fit Thresholds				Rate of Model Acceptance based on Fit Thresholds			
			CFI		RMSEA		CFI		RMSEA	
			≥.90	≥.95	≤.08	≤.05	≥.90	≥.95	≤.08	≤.05
	Klauer et al. (2010) - Study 1	12%	31%	11%	44%	16%	4%	1%	5%	2%
	Klauer et al. (2010) - Study 2	43%	7%	0%	14%	0%	3%	0%	6%	0%
	Miyake et al. (2000)	83%	24%	9%	57%	14%	20%	7%	47%	12%
	Median	40%	44%	10%	57%	15%	13%	5%	19%	4%
	Mean	45%	48%	19%	57%	16%	25%	8%	32%	7%
Inhibition-Shifting Merged	de Frias et al. (2009) - CE	43%	62%	44%	59%	41%	27%	19%	25%	18%
	de Frias et al. (2009) - CN	91%	83%	49%	84%	41%	76%	45%	76%	37%
	Fleming et al. (2016)	98%	0%	0%	23%	0%	0%	0%	23%	0%
	Friedman et al. (2011)	100%	22%	0%	52%	0%	22%	0%	52%	0%
	Hedden & Yoon (2006)	67%	12%	3%	26%	5%	8%	2%	17%	3%
	Hull et al. (2008)	60%	0%	0%	0%	0%	0%	0%	0%	0%
	Ito et al. (2015)	100%	0%	0%	0%	0%	0%	0%	0%	0%
	Klauer et al. (2010) - Study 1	27%	3%	1%	14%	2%	1%	0%	4%	1%
	Klauer et al. (2010) - Study 2	80%	1%	0%	4%	0%	1%	0%	3%	0%
	Miyake et al. (2000)	94%	4%	1%	27%	3%	4%	1%	25%	3%
	Median	86%	4%	1%	25%	1%	3%	0%	20%	1%
	Mean	76%	19%	10%	29%	9%	14%	7%	23%	6%
Inhibition-Updating Merged	de Frias et al. (2009) - CE	33%	45%	28%	42%	25%	15%	9%	14%	8%
	de Frias et al. (2009) - CN	94%	83%	50%	84%	42%	78%	47%	79%	39%
	Fleming et al. (2016)	100%	4%	0%	58%	0%	4%	0%	58%	0%
	Friedman et al. (2011)	100%	27%	0%	58%	0%	27%	0%	58%	0%
	Hedden & Yoon (2006)	60%	12%	3%	26%	4%	7%	2%	16%	2%
	Hull et al. (2008)	24%	0%	0%	0%	0%	0%	0%	0%	0%
	Ito et al. (2015)	100%	39%	1%	72%	1%	39%	1%	72%	1%
	Klauer et al. (2010) - Study 1	44%	12%	4%	30%	8%	5%	2%	13%	4%
	Klauer et al. (2010) - Study 2	56%	0%	0%	1%	0%	0%	0%	1%	0%
	Miyake et al. (2000)	98%	13%	4%	47%	8%	13%	4%	46%	8%
	Median	77%	13%	2%	45%	3%	10%	2%	31%	2%
	Mean	71%	24%	9%	42%	9%	19%	7%	36%	6%
Shifting-Updating Merged	de Frias et al. (2009) - CE	35%	43%	28%	40%	25%	15%	10%	14%	9%
	de Frias et al. (2009) - CN	50%	40%	12%	42%	9%	20%	6%	21%	5%
	Fleming et al. (2016)	97%	0%	0%	0%	0%	0%	0%	0%	0%
	Friedman et al. (2011)	76%	0%	0%	0%	0%	0%	0%	0%	0%
	Hedden & Yoon (2006)	62%	13%	4%	28%	5%	8%	2%	17%	3%

Model	Study	% Converged	Percent of Bootstrapped Samples Meeting Fit Thresholds				Rate of Model Acceptance based on Fit Thresholds			
			CFI		RMSEA		CFI		RMSEA	
			≥.90	≥.95	≤.08	≤.05	≥.90	≥.95	≤.08	≤.05
	Hull et al. (2008)	54%	0%	0%	0%	0%	0%	0%	0%	0%
	Ito et al. (2015)	69%	0%	0%	0%	0%	0%	0%	0%	0%
	Klauer et al. (2010) - Study 1	40%	1%	0%	8%	0%	0%	0%	3%	0%
	Klauer et al. (2010) - Study 2	75%	0%	0%	1%	0%	0%	0%	1%	0%
	Miyake et al. (2000)	93%	4%	1%	27%	3%	4%	1%	25%	3%
	Median	66%	1%	0%	5%	0%	0%	0%	2%	0%
	Mean	65%	10%	5%	15%	4%	5%	2%	8%	2%
Unidimensional	de Frias et al. (2009) - CE	76%	40%	26%	40%	25%	30%	20%	30%	19%
	de Frias et al. (2009) - CN	98%	39%	12%	51%	11%	38%	12%	50%	11%
	Fleming et al. (2016)	100%	0%	0%	0%	0%	0%	0%	0%	0%
	Friedman et al. (2011)	100%	0%	0%	0%	0%	0%	0%	0%	0%
	Hedden & Yoon (2006)	100%	10%	3%	26%	5%	10%	3%	26%	5%
	Hull et al. (2008)	93%	0%	0%	0%	0%	0%	0%	0%	0%
	Ito et al. (2015)	100%	0%	0%	0%	0%	0%	0%	0%	0%
	Klauer et al. (2010) - Study 1	81%	0%	0%	6%	0%	0%	0%	5%	0%
	Klauer et al. (2010) - Study 2	98%	0%	0%	0%	0%	0%	0%	0%	0%
	Miyake et al. (2000)	100%	2%	0%	17%	1%	2%	0%	17%	1%
	Median	99%	0%	0%	3%	0%	0%	0%	3%	0%
	Mean	95%	9%	4%	14%	4%	8%	4%	13%	4%

Note. CE = Cognitively Elite; CFI = Comparative Fit Index; CI = Confidence Interval; CN = Cognitively Normal; RMSEA = Root Mean Square Error of Approximation.

Table S5. *Child/Adolescent Studies: Percent of Samples where Each Measurement Model was Selected based on Change in Fit Cutoffs for All 5,000 Bootstrapped Samples (Percent Model Selection) and for Only Samples Where the Model Converged (Percent Contingent Model Selection)*

| | | | Percent Model Selection: Percent of Bootstrapped Samples where Model was Selected based on ΔFit Cutoff | | | | Percent Contingent Model Selection: Percent of Bootstrapped Samples where the Model was Selected based on ΔFit Cutoff among Samples where the Model Converged | | | |
| | | | ΔCFI | | ΔRMSEA | | ΔCFI | | ΔRMSEA | |
	Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
Bifactor	Agostino et al. (2010)	78%	12%	7%	2%	2%	15%	9%	3%	2%
	Arán-Filippetti (2013)	34%	28%	18%	22%	17%	82%	53%	66%	50%
	Brydges et al. (2012)	3%	1%	1%	0%	0%	37%	29%	10%	6%
	Duan et al. (2010)	52%	29%	27%	11%	9%	48%	45%	18%	14%
	Lehto et al. (2003)	67%	11%	9%	3%	1%	17%	13%	4%	2%
	Miller et al. (2012)	9%	9%	9%	5%	3%	99%	98%	52%	37%
	Rose et al. (2012)	49%	17%	12%	3%	1%	35%	25%	6%	2%
	Usai et al. (2014)	82%	11%	10%	4%	3%	13%	12%	5%	4%
	Xu et al. (2013) - Ages 7-9	44%	5%	4%	2%	2%	12%	10%	6%	4%
	Xu et al. (2013) - Ages 10-12	32%	2%	1%	0%	0%	6%	4%	1%	1%
	Xu et al. (2013) - Ages 13-15	74%	0%	0%	0%	0%	0%	0%	0%	0%
	Median*	49%	11%	7%	2%	1%	17%	13%	6%	2%
	Mean*	48%	12%	9%	5%	4%	28%	21%	12%	9%
Nested Factor	Agostino et al. (2010)	100%	0%	0%	0%	0%	0%	0%	0%	0%
	Arán-Filippetti (2013)	73%	47%	57%	52%	56%	65%	78%	72%	78%
	Brydges et al. (2012)	8%	6%	6%	2%	2%	71%	68%	29%	20%
	Duan et al. (2010)	56%	17%	18%	20%	19%	26%	27%	30%	29%
	Lehto et al. (2003)	77%	9%	7%	2%	2%	11%	10%	3%	2%
	Miller et al. (2012)	14%	5%	5%	2%	1%	37%	33%	11%	9%
	Rose et al. (2012)	60%	45%	50%	47%	40%	75%	83%	78%	66%
	Usai et al. (2014)	94%	2%	2%	1%	1%	2%	2%	1%	1%
	Xu et al. (2013) - Ages 7-9	46%	26%	25%	19%	17%	57%	55%	41%	36%
	Xu et al. (2013) - Ages 10-12	34%	13%	12%	6%	4%	38%	34%	17%	13%

			Percent Model Selection: Percent of Bootstrapped Samples where Model was Selected based on ΔFit Cutoff				Percent Contingent Model Selection: Percent of Bootstrapped Samples where the Model was Selected based on ΔFit Cutoff among Samples where the Model Converged			
			ΔCFI		ΔRMSEA		ΔCFI		ΔRMSEA	
	Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
	Xu et al. (2013) - Ages 13-15	76%	18%	14%	1%	1%	24%	18%	2%	1%
	Median*	60%	17%	14%	6%	4%	38%	34%	29%	20%
	Mean*	59%	20%	21%	17%	16%	41%	42%	30%	27%
Three-Factor	Agostino et al. (2010)	34%	6%	4%	2%	1%	17%	13%	6%	4%
	Arán-Filippetti (2013)	65%	4%	1%	0%	0%	6%	1%	0%	0%
	Brydges et al. (2012)	2%	1%	0%	0%	0%	25%	20%	2%	4%
	Duan et al. (2010)	21%	20%	19%	9%	8%	84%	77%	36%	33%
	Lehto et al. (2003)	86%	45%	39%	19%	13%	52%	46%	22%	15%
	Miller et al. (2012)	86%	64%	56%	9%	3%	74%	64%	11%	3%
	Rose et al. (2012)	60%	13%	10%	1%	2%	21%	16%	2%	3%
	Usai et al. (2014)	24%	7%	6%	2%	2%	29%	24%	7%	6%
	Xu et al. (2013) - Ages 7-9	15%	1%	0%	0%	0%	4%	2%	0%	1%
	Xu et al. (2013) - Ages 10-12	14%	0%	0%	0%	0%	3%	2%	1%	0%
	Xu et al. (2013) - Ages 13-15	26%	6%	4%	1%	1%	22%	17%	5%	3%
	Median*	26%	6%	4%	1%	1%	21%	16%	2%	3%
	Mean*	36%	10%	9%	4%	3%	26%	21%	8%	7%
Inhibition-Shifting Merged	Agostino et al. (2010)	47%	0%	0%	0%	0%	1%	0%	0%	0%
	Arán-Filippetti (2013)	100%	5%	4%	1%	0%	5%	4%	1%	0%
	Brydges et al. (2012)	89%	36%	26%	5%	2%	41%	30%	5%	2%
	Duan et al. (2010)	33%	8%	9%	15%	15%	20%	23%	40%	39%
	Lehto et al. (2003)	98%	14%	17%	24%	24%	14%	17%	25%	25%
	Miller et al. (2012)	88%	2%	3%	15%	14%	2%	4%	16%	16%
	Rose et al. (2012)	92%	6%	6%	5%	6%	6%	6%	6%	7%
	Usai et al. (2014)	35%	1%	1%	1%	0%	4%	3%	1%	1%
	Xu et al. (2013) - Ages 7-9	58%	10%	9%	5%	4%	17%	15%	8%	7%
	Xu et al. (2013) - Ages 10-12	69%	20%	17%	7%	5%	29%	24%	11%	8%

		Percent Model Selection: Percent of Bootstrapped Samples where Model was Selected based on ΔFit Cutoff				Percent Contingent Model Selection: Percent of Bootstrapped Samples where the Model was Selected based on ΔFit Cutoff among Samples where the Model Converged			
		ΔCFI		ΔRMSEA		ΔCFI		ΔRMSEA	
Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
Xu et al. (2013) - Ages 13-15	98%	57%	58%	43%	33%	58%	59%	44%	33%
Median*	89%	10%	9%	5%	5%	17%	17%	8%	7%
Mean*	76%	17%	16%	12%	10%	21%	20%	16%	13%

Inhibition-Updating Merged

Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
Agostino et al. (2010)	59%	1%	0%	1%	0%	1%	1%	1%	1%
Arán-Filippetti (2013)	64%	0%	0%	0%	0%	1%	1%	0%	0%
Brydges et al. (2012)	6%	0%	0%	0%	0%	0%	0%	0%	0%
Duan et al. (2010)	35%	5%	5%	3%	2%	11%	11%	7%	6%
Lehto et al. (2003)	94%	10%	13%	16%	15%	11%	14%	17%	16%
Miller et al. (2012)	93%	0%	0%	0%	0%	0%	0%	0%	0%
Rose et al. (2012)	87%	13%	15%	11%	7%	15%	17%	12%	8%
Usai et al. (2014)	52%	4%	4%	2%	1%	8%	7%	3%	2%
Xu et al. (2013) - Ages 7-9	35%	2%	2%	1%	0%	5%	5%	2%	1%
Xu et al. (2013) - Ages 10-12	40%	4%	3%	1%	1%	9%	7%	2%	1%
Xu et al. (2013) - Ages 13-15	78%	7%	6%	2%	1%	8%	8%	3%	2%
Median*	59%	4%	3%	1%	1%	8%	7%	2%	1%
Mean*	55%	5%	5%	4%	3%	7%	7%	5%	4%

Shifting-Updating Merged

Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
Agostino et al. (2010)	99%	77%	80%	78%	71%	78%	81%	80%	72%
Arán-Filippetti (2013)	100%	14%	12%	6%	3%	14%	12%	6%	3%
Brydges et al. (2012)	54%	5%	3%	0%	0%	10%	5%	1%	0%
Duan et al. (2010)	44%	13%	13%	13%	12%	26%	26%	26%	25%
Lehto et al. (2003)	97%	9%	11%	16%	15%	9%	11%	17%	16%
Miller et al. (2012)	98%	19%	26%	63%	62%	19%	26%	64%	63%
Rose et al. (2012)	90%	4%	4%	2%	2%	4%	4%	2%	2%
Usai et al. (2014)	75%	50%	49%	35%	28%	64%	63%	45%	36%
Xu et al. (2013) - Ages 7-9	56%	7%	6%	3%	2%	13%	10%	5%	4%
Xu et al. (2013) - Ages 10-12	51%	6%	5%	2%	1%	12%	9%	4%	3%

| | | Percent Model Selection: Percent of Bootstrapped Samples where Model was Selected based on ΔFit Cutoff | | | | Percent Contingent Model Selection: Percent of Bootstrapped Samples where the Model was Selected based on ΔFit Cutoff among Samples where the Model Converged | | | |
| | | ΔCFI | | ΔRMSEA | | ΔCFI | | ΔRMSEA | |
Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
Xu et al. (2013) - Ages 13-15	51%	1%	1%	0%	0%	3%	3%	1%	0%
Median*	56%	7%	6%	3%	2%	12%	10%	5%	3%
Mean*	71%	15%	15%	13%	12%	19%	18%	16%	14%
Unidimensional									
Agostino et al. (2010)	100%	5%	8%	16%	25%	5%	8%	16%	25%
Arán-Filippetti (2013)	100%	2%	8%	19%	23%	2%	8%	19%	23%
Brydges et al. (2012)	100%	51%	64%	92%	96%	51%	64%	92%	96%
Duan et al. (2010)	74%	9%	10%	30%	35%	10%	12%	35%	41%
Lehto et al. (2003)	100%	3%	4%	19%	30%	3%	4%	19%	30%
Miller et al. (2012)	99%	1%	1%	6%	16%	1%	1%	6%	16%
Rose et al. (2012)	100%	2%	3%	31%	43%	2%	3%	31%	43%
Usai et al. (2014)	95%	23%	27%	55%	65%	24%	28%	56%	66%
Xu et al. (2013) - Ages 7-9	100%	49%	54%	70%	75%	49%	54%	70%	75%
Xu et al. (2013) - Ages 10-12	100%	55%	63%	83%	88%	55%	63%	83%	88%
Xu et al. (2013) - Ages 13-15	100%	11%	16%	52%	65%	11%	16%	52%	65%
Median*	100%	9%	10%	31%	43%	10%	12%	35%	43%
Mean*	97%	21%	26%	46%	53%	21%	26%	46%	54%

* *Note*. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation.

*Median and Mean values exclude the two preschool articles listed in the table (Miller et al., 2012; Usai et al., 2014).

Table S6. *Adult Studies: Percent of Samples where Each Measurement Model was Selected based on Change in Fit Cutoffs for All 5,000 Bootstrapped Samples (Percent Model Selection) and for Only Samples Where the Model Converged (Percent Contingent Model Selection)*

| | Study | % Converged | Percent Model Selection: Percent of Bootstrapped Samples where Model was Selected based on ΔFit Cutoff | | | | Percent Contingent Model Selection: Percent of Bootstrapped Samples where the Model was Selected based on ΔFit Cutoff among Samples where the Model Converged | | | |
| | | | ΔCFI | | ΔRMSEA | | ΔCFI | | ΔRMSEA | |
			≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
Bifactor	de Frias et al. (2009) - CE	68%	7%	6%	3%	3%	9%	8%	4%	4%
	de Frias et al. (2009) - CN	98%	1%	0%	0%	0%	1%	0%	0%	0%
	Fleming et al. (2016)	8%	5%	4%	0%	0%	62%	47%	4%	3%
	Friedman et al. (2011)	12%	12%	11%	3%	1%	99%	85%	22%	6%
	Hedden & Yoon (2006)	5%	2%	2%	0%	0%	38%	33%	7%	5%
	Hull et al. (2008)	6%	5%	5%	2%	2%	83%	76%	33%	27%
	Ito et al. (2015)	6%	5%	5%	1%	1%	91%	78%	18%	9%
	Klauer et al. (2010) - Study 1	21%	2%	2%	1%	1%	8%	7%	4%	4%
	Klauer et al. (2010) - Study 2	5%	5%	5%	3%	2%	99%	96%	67%	50%
	Miyake et al. (2000)	13%	8%	8%	3%	2%	63%	58%	19%	15%
	Median	10%	5%	5%	2%	1%	62%	52%	13%	5%
	Mean	24%	5%	5%	2%	1%	55%	49%	18%	12%
Nested Factor	de Frias et al. (2009) - CE	71%	20%	19%	16%	15%	23%	23%	19%	18%
	de Frias et al. (2009) - CN	98%	18%	11%	9%	7%	18%	12%	9%	7%
	Fleming et al. (2016)	89%	68%	61%	22%	10%	76%	69%	24%	12%
	Friedman et al. (2011)	96%	39%	30%	12%	4%	41%	31%	12%	4%
	Hedden & Yoon (2006)	5%	3%	3%	1%	1%	58%	60%	24%	15%
	Hull et al. (2008)	25%	22%	22%	20%	17%	87%	88%	80%	68%
	Ito et al. (2015)	96%	70%	62%	10%	3%	74%	64%	11%	3%
	Klauer et al. (2010) - Study 1	22%	21%	21%	17%	16%	83%	83%	69%	65%
	Klauer et al. (2010) - Study 2	34%	21%	20%	8%	5%	63%	58%	23%	15%
	Miyake et al. (2000)	34%	17%	16%	6%	4%	48%	46%	19%	12%
	Median	53%	21%	20%	11%	6%	61%	59%	21%	14%

	Study	% Converged	Percent Model Selection: Percent of Bootstrapped Samples where Model was Selected based on ΔFit Cutoff				Percent Contingent Model Selection: Percent of Bootstrapped Samples where the Model was Selected based on ΔFit Cutoff among Samples where the Model Converged			
			ΔCFI		ΔRMSEA		ΔCFI		ΔRMSEA	
			≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
	Mean	57%	30%	26%	12%	8%	57%	53%	29%	22%
Three-Factor	de Frias et al. (2009) - CE	7%	1%	1%	1%	1%	11%	9%	6%	6%
	de Frias et al. (2009) - CN	37%	5%	6%	2%	2%	14%	15%	6%	5%
	Fleming et al. (2016)	94%	26%	34%	64%	58%	28%	36%	69%	62%
	Friedman et al. (2011)	80%	47%	58%	74%	65%	59%	73%	93%	82%
	Hedden & Yoon (2006)	29%	6%	4%	0%	0%	19%	13%	2%	1%
	Hull et al. (2008)	17%	10%	10%	4%	3%	59%	56%	21%	15%
	Ito et al. (2015)	52%	19%	26%	26%	14%	37%	51%	49%	27%
	Klauer et al. (2010) - Study 1	12%	8%	8%	4%	3%	61%	59%	28%	22%
	Klauer et al. (2010) - Study 2	43%	29%	29%	21%	13%	67%	68%	49%	30%
	Miyake et al. (2000)	83%	44%	40%	15%	9%	53%	48%	18%	11%
	Median	40%	15%	18%	9%	6%	45%	50%	24%	18%
	Mean	45%	20%	22%	21%	17%	41%	43%	34%	26%
Inhibition-Shifting Merged	de Frias et al. (2009) - CE	43%	21%	20%	17%	16%	41%	40%	34%	32%
	de Frias et al. (2009) - CN	91%	35%	38%	37%	35%	39%	42%	40%	38%
	Fleming et al. (2016)	98%	0%	0%	2%	4%	0%	0%	2%	4%
	Friedman et al. (2011)	100%	0%	0%	5%	13%	0%	0%	5%	13%
	Hedden & Yoon (2006)	67%	15%	13%	4%	2%	22%	19%	6%	3%
	Hull et al. (2008)	60%	29%	29%	30%	28%	47%	47%	49%	45%
	Ito et al. (2015)	100%	0%	0%	0%	0%	0%	0%	0%	0%
	Klauer et al. (2010) - Study 1	27%	12%	12%	12%	12%	40%	41%	39%	40%
	Klauer et al. (2010) - Study 2	80%	25%	26%	37%	40%	31%	32%	46%	50%
	Miyake et al. (2000)	94%	3%	4%	7%	6%	3%	4%	7%	6%
	Median	86%	14%	13%	9%	12%	27%	26%	21%	22%
	Mean	76%	14%	14%	15%	16%	22%	23%	23%	23%
Inhibition-Updating Merged	de Frias et al. (2009) - CE	33%	3%	3%	2%	2%	9%	9%	6%	5%
	de Frias et al. (2009) - CN	94%	37%	39%	38%	35%	39%	41%	40%	37%

		Percent Model Selection: Percent of Bootstrapped Samples where Model was Selected based on ΔFit Cutoff				Percent Contingent Model Selection: Percent of Bootstrapped Samples where the Model was Selected based on ΔFit Cutoff among Samples where the Model Converged			
		ΔCFI		ΔRMSEA		ΔCFI		ΔRMSEA	
Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
Fleming et al. (2016)	100%	1%	1%	12%	27%	1%	1%	12%	27%
Friedman et al. (2011)	100%	1%	1%	6%	18%	1%	1%	6%	18%
Hedden & Yoon (2006)	60%	9%	8%	1%	0%	15%	13%	2%	1%
Hull et al. (2008)	24%	7%	7%	9%	8%	29%	30%	37%	31%
Ito et al. (2015)	100%	5%	7%	63%	83%	5%	7%	63%	83%
Klauer et al. (2010) - Study 1	44%	29%	28%	26%	23%	58%	58%	53%	46%
Klauer et al. (2010) - Study 2	56%	7%	7%	8%	8%	13%	13%	14%	14%
Miyake et al. (2000)	98%	22%	26%	44%	41%	23%	26%	44%	41%
Median	77%	7%	7%	10%	20%	14%	13%	26%	29%
Mean	71%	12%	13%	21%	24%	19%	20%	28%	30%

Shifting-Updating Merged

Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
de Frias et al. (2009) - CE	35%	4%	4%	2%	2%	10%	9%	6%	4%
de Frias et al. (2009) - CN	50%	0%	0%	0%	0%	1%	1%	0%	0%
Fleming et al. (2016)	97%	0%	0%	0%	0%	0%	0%	0%	0%
Friedman et al. (2011)	76%	0%	0%	0%	0%	0%	0%	0%	0%
Hedden & Yoon (2006)	62%	21%	17%	4%	2%	34%	28%	6%	3%
Hull et al. (2008)	54%	14%	12%	1%	1%	24%	21%	2%	2%
Ito et al. (2015)	69%	0%	0%	0%	0%	0%	0%	0%	0%
Klauer et al. (2010) - Study 1	40%	6%	6%	2%	1%	14%	13%	4%	2%
Klauer et al. (2010) - Study 2	75%	8%	8%	8%	9%	10%	10%	11%	11%
Miyake et al. (2000)	93%	5%	5%	9%	8%	5%	6%	10%	9%
Median	66%	4%	5%	1%	1%	7%	7%	3%	2%
Mean	65%	6%	5%	3%	2%	10%	9%	4%	3%

Unidimensional

Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
de Frias et al. (2009) - CE	76%	44%	46%	58%	61%	49%	51%	65%	68%
de Frias et al. (2009) - CN	98%	3%	5%	13%	20%	3%	5%	13%	20%
Fleming et al. (2016)	100%	0%	0%	0%	0%	0%	0%	0%	0%
Friedman et al. (2011)	100%	0%	0%	0%	0%	0%	0%	0%	0%
Hedden & Yoon (2006)	100%	44%	54%	89%	95%	44%	54%	89%	95%

		Percent Model Selection: Percent of Bootstrapped Samples where Model was Selected based on ΔFit Cutoff				Percent Contingent Model Selection: Percent of Bootstrapped Samples where the Model was Selected based on ΔFit Cutoff among Samples where the Model Converged			
		ΔCFI		ΔRMSEA		ΔCFI		ΔRMSEA	
Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
Hull et al. (2008)	93%	13%	15%	33%	42%	14%	16%	35%	44%
Ito et al. (2015)	100%	0%	0%	0%	0%	0%	0%	0%	0%
Klauer et al. (2010) - Study 1	81%	22%	23%	39%	44%	25%	26%	43%	49%
Klauer et al. (2010) - Study 2	98%	5%	6%	15%	23%	5%	6%	15%	23%
Miyake et al. (2000)	100%	1%	1%	17%	30%	1%	1%	17%	30%
Median	99%	4%	5%	16%	27%	4%	5%	16%	27%
Mean	95%	13%	15%	26%	32%	14%	16%	28%	33%

Table S7. *Child/Adolescent Studies: Mean Fit Indices (95% CIs) for Converged Models by Measurement Model and Study*

Model	Study	% Converged	CFI	95% CI	RMSEA	95% CI
Bifactor	Agostino et al. (2010)	78%	0.96	(0.88, 1)	0.08	(0, 0.14)
	Arán-Filippetti (2013)	34%	0.99	(0.97, 1)	0.06	(0, 0.09)
	Brydges et al. (2012)	3%	0.94	(0.88, 1)	0.06	(0.02, 0.09)
	Duan et al. (2010)	52%	0.85	(0.73, 0.96)	0.23	(0.12, 0.33)
	Lehto et al. (2003)	67%	0.91	(0.77, 1)	0.09	(0, 0.15)
	Miller et al. (2012)	9%	0.90	(0.83, 0.96)	0.10	(0.06, 0.13)
	Rose et al. (2012)	49%	0.87	(0.74, 0.96)	0.09	(0.05, 0.13)
	Usai et al. (2014)	82%	0.88	(0.71, 1)	0.09	(0, 0.16)
	Xu et al. (2013) - Ages 7-9	44%	0.95	(0.82, 1)	0.05	(0, 0.12)
	Xu et al. (2013) - Ages 10-12	32%	0.93	(0.78, 1)	0.06	(0, 0.12)
	Xu et al. (2013) - Ages 13-15	74%	0.85	(0.70, 0.97)	0.11	(0.05, 0.17)
Nested Factor	Agostino et al. (2010)	100%	0.90	(0.79, 0.98)	0.10	(0.05, 0.16)
	Arán-Filippetti (2013)	73%	0.98	(0.95, 0.99)	0.07	(0.04, 0.1)
	Brydges et al. (2012)	8%	0.94	(0.86, 1)	0.06	(0.01, 0.09)
	Duan et al. (2010)	56%	0.82	(0.70, 0.94)	0.23	(0.13, 0.33)
	Lehto et al. (2003)	77%	0.89	(0.74, 1)	0.09	(0, 0.15)
	Miller et al. (2012)	14%	0.83	(0.74, 0.91)	0.12	(0.09, 0.15)
	Rose et al. (2012)	60%	0.86	(0.74, 0.96)	0.09	(0.05, 0.13)
	Usai et al. (2014)	94%	0.83	(0.63, 0.99)	0.10	(0.03, 0.16)
	Xu et al. (2013) - Ages 7-9	46%	0.95	(0.82, 1)	0.05	(0, 0.11)
	Xu et al. (2013) - Ages 10-12	34%	0.93	(0.80, 1)	0.05	(0, 0.11)
	Xu et al. (2013) - Ages 13-15	76%	0.86	(0.70, 0.98)	0.10	(0.04, 0.16)
Three-Factor	Agostino et al. (2010)	34%	0.96	(0.88, 1)	0.06	(0, 0.13)
	Arán-Filippetti (2013)	65%	0.93	(0.89, 0.96)	0.12	(0.09, 0.15)
	Brydges et al. (2012)	2%	0.93	(0.86, 0.99)	0.06	(0.02, 0.09)
	Duan et al. (2010)	21%	0.87	(0.76, 0.97)	0.22	(0.11, 0.31)
	Lehto et al. (2003)	86%	0.91	(0.78, 1)	0.07	(0, 0.13)
	Miller et al. (2012)	86%	0.83	(0.74, 0.91)	0.11	(0.08, 0.14)
	Rose et al. (2012)	60%	0.77	(0.63, 0.89)	0.11	(0.07, 0.14)
	Usai et al. (2014)	24%	0.91	(0.75, 1)	0.08	(0, 0.14)

Model	Study	% Converged	CFI	95% CI	RMSEA	95% CI
	Xu et al. (2013) - Ages 7-9	15%	0.92	(0.74, 1)	0.06	(0, 0.13)
	Xu et al. (2013) - Ages 10-12	14%	0.93	(0.76, 1)	0.06	(0, 0.12)
	Xu et al. (2013) - Ages 13-15	26%	0.87	(0.72, 1)	0.09	(0, 0.15)
Inhibition-Shifting Merged	Agostino et al. (2010)	47%	0.90	(0.80, 0.98)	0.10	(0.04, 0.15)
	Arán-Filippetti (2013)	100%	0.92	(0.88, 0.95)	0.12	(0.09, 0.15)
	Brydges et al. (2012)	89%	0.90	(0.81, 0.98)	0.07	(0.03, 0.10)
	Duan et al. (2010)	33%	0.81	(0.65, 0.95)	0.23	(0.12, 0.32)
	Lehto et al. (2003)	98%	0.88	(0.72, 1)	0.09	(0, 0.14)
	Miller et al. (2012)	88%	0.78	(0.67, 0.87)	0.13	(0.09, 0.15)
	Rose et al. (2012)	92%	0.73	(0.58, 0.87)	0.11	(0.08, 0.15)
	Usai et al. (2014)	35%	0.84	(0.66, 1)	0.09	(0.01, 0.15)
	Xu et al. (2013) - Ages 7-9	58%	0.90	(0.73, 1)	0.06	(0, 0.12)
	Xu et al. (2013) - Ages 10-12	69%	0.92	(0.75, 1)	0.06	(0, 0.11)
	Xu et al. (2013) - Ages 13-15	98%	0.85	(0.69, 0.98)	0.09	(0.03, 0.14)
Inhibition-Updating Merged	Agostino et al. (2010)	59%	0.90	(0.80, 0.98)	0.10	(0.04, 0.15)
	Arán-Filippetti (2013)	64%	0.91	(0.87, 0.95)	0.13	(0.10, 0.15)
	Brydges et al. (2012)	6%	0.91	(0.81, 0.98)	0.06	(0.03, 0.09)
	Duan et al. (2010)	35%	0.78	(0.62, 0.92)	0.25	(0.15, 0.35)
	Lehto et al. (2003)	94%	0.87	(0.70, 0.99)	0.09	(0.02, 0.14)
	Miller et al. (2012)	93%	0.74	(0.63, 0.84)	0.13	(0.10, 0.16)
	Rose et al. (2012)	87%	0.74	(0.58, 0.88)	0.11	(0.08, 0.15)
	Usai et al. (2014)	52%	0.84	(0.64, 1)	0.09	(0, 0.15)
	Xu et al. (2013) - Ages 7-9	35%	0.90	(0.71, 1)	0.06	(0, 0.12)
	Xu et al. (2013) - Ages 10-12	40%	0.91	(0.73, 1)	0.06	(0, 0.11)
	Xu et al. (2013) - Ages 13-15	78%	0.81	(0.65, 0.95)	0.11	(0.05, 0.15)
Shifting-Updating Merged	Agostino et al. (2010)	99%	0.96	(0.87, 1)	0.06	(0, 0.12)
	Arán-Filippetti (2013)	100%	0.92	(0.88, 0.95)	0.12	(0.09, 0.14)
	Brydges et al. (2012)	54%	0.90	(0.80, 0.98)	0.07	(0.03, 0.10)
	Duan et al. (2010)	44%	0.78	(0.64, 0.92)	0.24	(0.15, 0.33)
	Lehto et al. (2003)	97%	0.87	(0.72, 0.99)	0.09	(0.02, 0.14)
	Miller et al. (2012)	98%	0.80	(0.70, 0.89)	0.12	(0.09, 0.15)

Model	Study	% Converged	CFI	95% CI	RMSEA	95% CI
	Rose et al. (2012)	90%	0.72	(0.56, 0.85)	0.12	(0.08, 0.15)
	Usai et al. (2014)	75%	0.89	(0.72, 1)	0.07	(0, 0.14)
	Xu et al. (2013) - Ages 7-9	56%	0.90	(0.71, 1)	0.06	(0, 0.12)
	Xu et al. (2013) - Ages 10-12	51%	0.91	(0.75, 1)	0.06	(0, 0.11)
	Xu et al. (2013) - Ages 13-15	51%	0.81	(0.63, 0.95)	0.11	(0.05, 0.16)
Unidimensional	Agostino et al. (2010)	100%	0.90	(0.79, 0.98)	0.09	(0.04, 0.14)
	Arán-Filippetti (2013)	100%	0.91	(0.87, 0.94)	0.12	(0.10, 0.15)
	Brydges et al. (2012)	100%	0.90	(0.80, 0.98)	0.07	(0.03, 0.1)
	Duan et al. (2010)	74%	0.73	(0.56, 0.89)	0.26	(0.16, 0.35)
	Lehto et al. (2003)	100%	0.83	(0.66, 0.97)	0.10	(0.04, 0.15)
	Miller et al. (2012)	99%	0.73	(0.61, 0.83)	0.14	(0.11, 0.17)
	Rose et al. (2012)	100%	0.70	(0.53, 0.84)	0.12	(0.08, 0.15)
	Usai et al. (2014)	95%	0.83	(0.64, 1)	0.09	(0, 0.14)
	Xu et al. (2013) - Ages 7-9	100%	0.90	(0.72, 1)	0.06	(0, 0.12)
	Xu et al. (2013) - Ages 10-12	100%	0.91	(0.74, 1)	0.06	(0, 0.11)
	Xu et al. (2013) - Ages 13-15	100%	0.80	(0.63, 0.95)	0.10	(0.05, 0.15)

Note. CFI = Comparative Fit Index; CI = Confidence Interval; RMSEA = Root Mean Square Error of Approximation.

Table S8. *Adult Studies: Mean Fit Indices (95% CIs) for Converged Models by Measurement Model and Study*

Model	Study	% Converged	CFI	95% CI	RMSEA	95% CI
Bifactor	de Frias et al. (2009) - CE	68%	0.89	(0.65, 1)	0.09	(0, 0.20)
	de Frias et al. (2009) - CN	98%	0.95	(0.86, 1)	0.05	(0, 0.11)
	Fleming et al. (2016)	8%	0.94	(0.9, 0.98)	0.05	(0.03, 0.08)
	Friedman et al. (2011)	12%	0.97	(0.94, 0.99)	0.05	(0.03, 0.07)
	Hedden & Yoon (2006)	5%	0.88	(0.73, 1)	0.09	(0, 0.14)
	Hull et al. (2008)	6%	0.74	(0.63, 0.85)	0.15	(0.10, 0.19)
	Ito et al. (2015)	6%	0.95	(0.91, 0.99)	0.06	(0.03, 0.08)
	Klauer et al (2010) - Study 1	21%	0.87	(0.69, 1)	0.08	(0, 0.14)
	Klauer et al (2010) - Study 2	5%	0.90	(0.79, 0.99)	0.08	(0.03, 0.12)
	Miyake et al. (2000)	13%	0.90	(0.76, 1)	0.07	(0, 0.11)
Nested Factor	de Frias et al. (2009) - CE	71%	0.9	(0.65, 1)	0.08	(0, 0.18)
	de Frias et al. (2009) - CN	98%	0.96	(0.86, 1)	0.05	(0, 0.10)
	Fleming et al. (2016)	89%	0.93	(0.86, 0.98)	0.06	(0.03, 0.08)
	Friedman et al. (2011)	96%	0.94	(0.91, 0.97)	0.06	(0.04, 0.08)
	Hedden & Yoon (2006)	5%	0.87	(0.67, 1)	0.09	(0.01, 0.14)
	Hull et al. (2008)	25%	0.71	(0.59, 0.84)	0.15	(0.11, 0.19)
	Ito et al. (2015)	96%	0.93	(0.88, 0.97)	0.07	(0.05, 0.09)
	Klauer et al (2010) - Study 1	22%	0.88	(0.67, 1)	0.07	(0, 0.14)
	Klauer et al (2010) - Study 2	34%	0.83	(0.72, 0.93)	0.1	(0.06, 0.14)
	Miyake et al. (2000)	34%	0.86	(0.69, 1)	0.07	(0, 0.12)
Three-Factor	de Frias et al. (2009) - CE	7%	0.93	(0.71, 1)	0.07	(0, 0.18)
	de Frias et al. (2009) - CN	37%	0.96	(0.88, 1)	0.05	(0, 0.10)
	Fleming et al. (2016)	94%	0.9	(0.83, 0.96)	0.06	(0.04, 0.08)
	Friedman et al. (2011)	80%	0.94	(0.91, 0.97)	0.06	(0.04, 0.07)
	Hedden & Yoon (2006)	29%	0.81	(0.64, 0.97)	0.1	(0.04, 0.14)
	Hull et al. (2008)	17%	0.62	(0.48, 0.76)	0.16	(0.13, 0.20)
	Ito et al. (2015)	52%	0.92	(0.87, 0.96)	0.06	(0.05, 0.08)
	Klauer et al (2010) - Study 1	12%	0.84	(0.63, 1)	0.08	(0, 0.14)
	Klauer et al (2010) - Study 2	43%	0.82	(0.71, 0.93)	0.1	(0.06, 0.14)
	Miyake et al. (2000)	83%	0.84	(0.67, 0.99)	0.07	(0.01, 0.11)

Model	Study	% Converged	CFI	95% CI	RMSEA	95% CI
Inhibition-Shifting Merged	de Frias et al. (2009) - CE	43%	0.91	(0.69, 1)	0.06	(0, 0.16)
	de Frias et al. (2009) - CN	91%	0.94	(0.84, 1)	0.05	(0, 0.10)
	Fleming et al. (2016)	98%	0.79	(0.7, 0.87)	0.09	(0.07, 0.11)
	Friedman et al. (2011)	100%	0.88	(0.84, 0.92)	0.08	(0.07, 0.09)
	Hedden & Yoon (2006)	67%	0.79	(0.57, 0.96)	0.1	(0.04, 0.14)
	Hull et al. (2008)	60%	0.56	(0.42, 0.71)	0.17	(0.13, 0.20)
	Ito et al. (2015)	100%	0.78	(0.71, 0.84)	0.11	(0.09, 0.12)
	Klauer et al (2010) - Study 1	27%	0.67	(0.43, 0.9)	0.11	(0.05, 0.16)
	Klauer et al (2010) - Study 2	80%	0.76	(0.64, 0.88)	0.11	(0.08, 0.15)
	Miyake et al. (2000)	94%	0.74	(0.56, 0.92)	0.09	(0.05, 0.13)
Inhibition-Updating Merged	de Frias et al. (2009) - CE	33%	0.86	(0.59, 1)	0.09	(0, 0.19)
	de Frias et al. (2009) - CN	94%	0.94	(0.84, 1)	0.05	(0, 0.10)
	Fleming et al. (2016)	100%	0.84	(0.75, 0.91)	0.08	(0.06, 0.10)
	Friedman et al. (2011)	100%	0.89	(0.84, 0.93)	0.08	(0.06, 0.09)
	Hedden & Yoon (2006)	60%	0.79	(0.57, 0.95)	0.1	(0.04, 0.14)
	Hull et al. (2008)	24%	0.57	(0.43, 0.73)	0.17	(0.13, 0.20)
	Ito et al. (2015)	100%	0.89	(0.83, 0.94)	0.07	(0.05, 0.09)
	Klauer et al (2010) - Study 1	44%	0.76	(0.55, 0.97)	0.09	(0.03, 0.15)
	Klauer et al (2010) - Study 2	56%	0.71	(0.57, 0.85)	0.12	(0.09, 0.16)
	Miyake et al. (2000)	98%	0.8	(0.61, 0.97)	0.08	(0.03, 0.12)
Shifting-Updating Merged	de Frias et al. (2009) - CE	35%	0.86	(0.61, 1)	0.09	(0, 0.18)
	de Frias et al. (2009) - CN	50%	0.88	(0.74, 0.99)	0.08	(0.03, 0.13)
	Fleming et al. (2016)	97%	0.57	(0.47, 0.67)	0.13	(0.11, 0.15)
	Friedman et al. (2011)	76%	0.75	(0.69, 0.81)	0.12	(0.10, 0.13)
	Hedden & Yoon (2006)	62%	0.79	(0.6, 0.96)	0.09	(0.04, 0.14)
	Hull et al. (2008)	54%	0.48	(0.34, 0.64)	0.18	(0.15, 0.22)
	Ito et al. (2015)	69%	0.6	(0.51, 0.68)	0.14	(0.12, 0.16)
	Klauer et al (2010) - Study 1	40%	0.64	(0.38, 0.86)	0.12	(0.07, 0.17)
	Klauer et al (2010) - Study 2	75%	0.73	(0.6, 0.85)	0.12	(0.08, 0.15)
	Miyake et al. (2000)	93%	0.75	(0.55, 0.92)	0.09	(0.05, 0.13)

Model	Study	% Converged	CFI	95% CI	RMSEA	95% CI
Unidimensional	de Frias et al. (2009) - CE	76%	0.85	(0.57, 1)	0.09	(0, 0.18)
	de Frias et al. (2009) - CN	98%	0.88	(0.75, 0.99)	0.08	(0.02, 0.12)
	Fleming et al. (2016)	100%	0.55	(0.45, 0.66)	0.13	(0.11, 0.15)
	Friedman et al. (2011)	100%	0.75	(0.69, 0.81)	0.11	(0.10, 0.13)
	Hedden & Yoon (2006)	100%	0.78	(0.56, 0.96)	0.09	(0.04, 0.14)
	Hull et al. (2008)	93%	0.45	(0.31, 0.6)	0.19	(0.15, 0.22)
	Ito et al. (2015)	100%	0.6	(0.51, 0.69)	0.14	(0.12, 0.16)
	Klauer et al (2010) - Study 1	81%	0.58	(0.34, 0.82)	0.12	(0.07, 0.17)
	Klauer et al (2010) - Study 2	98%	0.65	(0.5, 0.79)	0.13	(0.10, 0.17)
	Miyake et al. (2000)	100%	0.7	(0.5, 0.88)	0.1	(0.06, 0.13)

Note. CFI = Comparative Fit Index; CI = Confidence Interval; RMSEA = Root Mean Square Error of Approximation.

Table S9. *Child/Adolescent Studies: Inter-factor Correlations and 95% Confidence Intervals for Converged Models*

| | Three-Factor | | | | | | Inh.-Shi. Merged | | Inh.-Upd. Merged | | Shi.-Upd. Merged | |
| | Upd. w/ Inh. | | Upd. w/ Shi. | | Shi. w/ Inh. | | Inh.-Shi. w/ Upd. | | Inh.-Upd. w/ Shi. | | Shi.-Upd. w/ Inh. | |
Study	r	95% C.I.	r	95% CI	r	95% CI	r	95% CI	r	95% CI	r	95% CI
Agostino et al. (2010)	0.72	(0.88, 0.91)	0.91	(0.78, 0.99)	0.65	(0.39, 0.86)	0.93	(0.79, 1)	0.92	(0.79, 1)	0.73	(0.55, 0.89)
Arán-Filippetti (2013)	0.89	(0.95, 0.94)	0.94	(0.76, 0.99)	0.9	(0.70, 0.98)	0.94	(0.9, 0.98)	0.96	(0.90, 0.98)	0.90	(0.84, 0.96)
Brydges et al. (2012)	0.64	(0.91, 0.89)	0.89	(0.78, 0.97)	0.83	(0.60, 0.97)	0.89	(0.76, 0.99)	0.96	(0.76, 0.99)	0.84	(0.59, 0.99)
Duan et al. (2010)	0.23	(0.57, 0.78)	0.78	(0.59, 0.94)	0.49	(0.12, 0.79)	0.77	(0.59, 0.93)	0.80	(0.59, 0.93)	0.40	(0.08, 0.74)
Lehto et al. (2003)	0.66	(0.92, 0.38)	0.38	(-0.79, 0.87)	0.36	(-0.78, 0.88)	0.75	(0.49, 0.96)	0.39	(0.49, 0.96)	0.71	(0.45, 0.94)
Miller et al. (2012)	0.42	(0.64, 0.81)	0.81	(0.65, 0.95)	0.53	(0.18, 0.82)	0.75	(0.54, 0.91)	0.83	(0.54, 0.91)	0.45	(0.22, 0.68)
Rose et al. (2012)	0.62	(0.93, 0.61)	0.61	(0.37, 0.85)	0.46	(0.01, 0.79)	0.72	(0.40, 0.97)	0.62	(0.40, 0.97)	0.65	(0.35, 0.95)
Usai et al. (2014)	0.61	(0.89, 0.76)	0.76	(0.50, 0.97)	0.40	(0.07, 0.79)	0.85	(0.58, 0.99)	0.75	(0.58, 0.99)	0.62	(0.36, 0.94)
Xu et al. (2013) - Ages 7-9	0.68	(0.95, 0.80)	0.80	(0.44, 0.98)	0.69	(0.26, 0.97)	0.85	(0.54, 1)	0.86	(0.54, 1)	0.77	(0.43, 0.98)
Xu et al. (2013) - Ages 10-12	0.76	(0.97, 0.74)	0.74	(0.47, 0.97)	0.69	(0.33, 0.96)	0.84	(0.58, 0.99)	0.81	(0.58, 0.99)	0.81	(0.52, 0.99)
Xu et al. (2013) - Ages 13-15	0.71	(0.93, 0.54)	0.54	(0.11, 0.88)	0.79	(0.48, 0.98)	0.71	(0.43, 0.94)	0.77	(0.43, 0.94)	0.85	(0.58, 0.99)

Note. Inh. = Inhibition; Shi. = Shifting; Upd. = Updating.

Table S10. *Adult Studies: Inter-factor Correlations and 95% Confidence Intervals for Converged Models*

| | Three-Factor | | | | | | Inh.-Shi. Merged | | Inh.-Upd. Merged | | Shi.-Upd. Merged | |
| | Upd. w/ Inh. | | Upd. w/ Shi. | | Shi. w/ Inh. | | Inh.-Shi. w/ Upd. | | Inh.-Upd. w/ Shi. | | Shi.-Upd. w/ Inh. | |
Study	r	95% CI	r	95% CI	r	95% CI	r	95% CI	r	95% CI	r	95% CI
de Frias et al. (2009) - CE	0.48	(-0.22, 0.89)	0.60	(0.26, 0.92)	0.46	(-0.25, 0.89)	0.65	(0.30, 0.97)	0.65	(0.26, 0.97)	0.56	(0.11, 0.96)
de Frias et al. (2009) - CN	0.62	(0.25, 0.93)	0.50	(0.25, 0.74)	0.56	(0.10, 0.93)	0.60	(0.37, 0.87)	0.53	(0.31, 0.79)	0.70	(0.32, 0.98)
Fleming et al. (2016)	0.58	(0.38, 0.80)	0.12	(-0.02, 0.27)	0.48	(0.29, 0.70)	0.21	(0.05, 0.37)	0.21	(0.03, 0.39)	0.60	(0.35, 0.90)
Friedman et al. (2011)	0.76	(0.65, 0.86)	0.38	(0.28, 0.47)	0.77	(0.66, 0.87)	0.48	(0.38, 0.57)	0.54	(0.44, 0.64)	0.92	(0.81, 1.00)
Hedden & Yoon (2006)	0.50	(0.06, 0.91)	0.81	(0.52, 0.98)	0.57	(0.13, 0.91)	0.83	(0.54, 0.99)	0.85	(0.59, 0.99)	0.61	(0.27, 0.96)
Hull et al. (2008)	0.41	(-0.02, 0.80)	-0.22	(-0.49, 0.15)	0.13	(-0.58, 0.72)	-0.10	(-0.53, 0.69)	-0.27	(-0.53, 0.16)	0.47	(0.09, 0.87)
Ito et al. (2015)	0.85	(0.71, 0.95)	0.23	(0.10, 0.35)	0.53	(0.38, 0.68)	0.33	(0.18, 0.49)	0.32	(0.20, 0.45)	0.76	(0.51, 0.99)
Klauer et al (2010) - Study 1	0.60	(0.31, 0.89)	0.21	(-0.17, 0.53)	0.48	(0.09, 0.83)	0.50	(0.11, 0.90)	0.40	(0, 0.78)	0.62	(0.22, 0.97)
Klauer et al (2010) - Study 2	0.34	(-0.02, 0.64)	-0.15	(-0.49, 0.16)	0.37	(-0.17, 0.79)	0.23	(-0.27, 0.62)	-0.15	(-0.47, 0.20)	0.33	(-0.06, 0.70)
Miyake et al. (2000)	0.61	(0.23, 0.93)	0.55	(0.22, 0.85)	0.41	(0.02, 0.78)	0.67	(0.31, 0.97)	0.56	(0.26, 0.86)	0.61	(0.26, 0.92)

Note. Inh. = Inhibition; Shi. = Shifting; Upd. = Updating.

Table S11. *Mean Observed Inter-Item Correlations for Indicators in Published Factor Models*

	Authors	Inhibition	Updating	Shifting
Child/Adolescent Studies	Agostino et al. (2010)	0.32	0.32	0.36
	Arán-Filippetti et al. (2013)	0.49	0.71	0.45
	Brydges et al. (2012)	0.08	0.36	0.25
	Duan et al. (2010)	0.36	0.75	0.48
	Lehto et al. (2003)	0.38	0.28	0.34
	Miller et al. (2012)	0.48	0.46	0.33
	Rose et al. (2012)	0.26	0.30	0.36
	Usai et al. (2014)	0.25	0.25	0.11
	Xu et al. (2013) – Ages 7 to 9	0.13	0.28	0.18
	Xu et al. (2013) – Ages 10 to 12	0.14	0.23	0.11
	Xu et al. (2013) – Ages 13 to 15	0.25	0.28	0.21
	Median	0.26	0.30	0.33
	Mean	0.29	0.41	0.29
Adult Studies	de Frias et al. (2009) – CE	0.07	0.52	0.07
	de Frias et al. (2009) – CN	0.04	0.49	0.24
	Fleming et al. (2016)	0.13	0.29	0.38
	Friedman et al. (2011)	0.21	0.37	0.45
	Hedden & Yoon (2006)	0.15	0.31	0.20
	Hull et al. (2008)	0.20	0.25	0.49
	Ito et al. (2015)	0.17	0.34	0.44
	Klauer et al. (2010) – Study 1	0.26	0.24	0.12
	Klauer et al. (2010 – Study 2	0.18	0.62	0.23
	Miyake et al. (2000)	0.20	0.25	0.28
	Median	0.18	0.33	0.26
	Mean	0.16	0.38	0.30
All Studies	Median	0.20	0.31	0.28
	Mean	0.23	0.39	0.29

Table S12. *Post-hoc Evaluation of Publication Bias: Determining the Rate of Originally Accepted Models Converging and Meeting Fit Thresholds among 5,000 Bootstrapped Samples*

Age Band	Model	Study	% Converged	Percent of Bootstrapped Samples Meeting Fit Thresholds				Rate of Model Acceptance based on Fit Thresholds			
				CFI		RMSEA		CFI		RMSEA	
				≥.90	≥.95	≤.08	≤.05	≥.90	≥.95	≤.08	≤.05
Child/Adolescent	Three-Factor	Agostino et al. (2010)	34%	94%	65%	65%	30%	32%	22%	22%	10%
		Arán-Filippetti (2013)	65%	92%	7%	0%	0%	60%	5%	0%	0%
		Duan et al. (2010)	21%	28%	7%	1%	0%	6%	1%	0%	0%
		Lehto et al. (2003)	86%	64%	32%	52%	22%	55%	28%	45%	19%
		Rose et al. (2012)	60%	2%	0%	5%	0%	1%	0%	3%	0%
	Shifting-Updating Merged	Miller et al. (2012)	98%	1%	0%	1%	0%	1%	0%	1%	0%
		Usai et al. (2014)	75%	50%	25%	52%	22%	38%	19%	39%	17%
	Unidimensional	Brydges et al. (2012)	100%	48%	11%	77%	14%	48%	11%	77%	14%
		Xu et al. (2013) - Ages 7-9	100%	55%	31%	67%	32%	55%	31%	67%	32%
		Xu et al. (2013) - Ages 10-12	100%	60%	33%	77%	37%	60%	33%	77%	37%
		Median	81%	53%	18%	52%	18%	43%	15%	31%	12%
		Mean	74%	49%	21%	40%	16%	36%	15%	33%	13%
Adult	Nested Factor	Fleming et al. (2016)	89%	81%	22%	97%	27%	72%	20%	86%	24%
		Friedman et al. (2011)	96%	100%	37%	99%	10%	96%	36%	95%	10%
		Ito et al. (2015)	96%	87%	14%	86%	6%	84%	13%	83%	6%
	Three-Factor	de Frias et al. (2009) - CE	7%	69%	48%	56%	39%	5%	3%	4%	3%
		Klauer et al. (2010) - Study 2	43%	7%	0%	14%	0%	3%	0%	6%	0%
		Miyake et al. (2000)	83%	24%	9%	57%	14%	20%	7%	47%	12%
	Inhibition-Updating Merged	Klauer et al. (2010) - Study 1	44%	12%	4%	30%	8%	5%	2%	13%	4%
	Shifting-Updating Merged	Hedden & Yoon (2006)	62%	13%	4%	28%	5%	8%	2%	17%	3%
		Median	73%	47%	12%	57%	9%	14%	5%	32%	5%
		Mean	65%	49%	17%	58%	14%	37%	10%	44%	8%

Note. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation.

Table S13. *Post-hoc Evaluation of Publication Bias: Determining the Rate of Researchers Re-selecting their Originally Selected Model among 5,000 Bootstrapped Samples*

| | | | | Percent Model Selection: Percent of Bootstrapped Samples where Model was Selected based on ΔFit Cutoff | | | | Percent Contingent Model Selection: Percent of Bootstrapped Samples where the Model was Selected based on ΔFit Cutoff among Samples where the Model Converged | | | |
| | | | | ΔCFI | | ΔRMSEA | | ΔCFI | | ΔRMSEA | |
Age Band	Model	Study	% Converged	≥.005	≥.010	≤-.010	≤-.015	≥.005	≥.010	≤-.010	≤-.015
Child/Adolescent	Three-Factor	Agostino et al. (2010)	34%	6%	4%	2%	1%	17%	13%	6%	4%
		Arán-Filippetti (2013)	65%	4%	1%	0%	0%	6%	1%	0%	0%
		Duan et al. (2010)	21%	20%	19%	9%	8%	84%	77%	36%	33%
		Lehto et al. (2003)	86%	45%	39%	19%	13%	52%	46%	22%	15%
		Rose et al. (2012)	60%	13%	10%	1%	2%	21%	16%	2%	3%
	Shifting-Updating Merged	Miller et al. (2012)	98%	19%	26%	63%	62%	19%	26%	64%	63%
		Usai et al. (2014)	75%	50%	49%	35%	28%	64%	63%	45%	36%
	Unidimensional	Brydges et al. (2012)	100%	51%	64%	92%	96%	51%	64%	92%	96%
		Xu et al. (2013) - Ages 7-9	100%	49%	54%	70%	75%	49%	54%	70%	75%
		Xu et al. (2013) - Ages 10-12	100%	55%	63%	83%	88%	55%	63%	83%	88%
		Median	81%	33%	33%	27%	21%	50%	50%	41%	35%
		Mean	74%	31%	33%	37%	37%	42%	42%	42%	41%
Adult	Nested Factor	Fleming et al. (2016)	89%	68%	61%	22%	10%	76%	69%	24%	12%
		Friedman et al. (2011)	96%	39%	30%	12%	4%	41%	31%	12%	4%
		Ito et al. (2015)	96%	70%	62%	10%	3%	74%	64%	11%	3%
	Three-Factor	de Frias et al. (2009) - CE	7%	1%	1%	1%	1%	11%	9%	6%	6%
		Klauer et al. (2010) - Study 2	43%	29%	29%	21%	13%	67%	68%	49%	30%
		Miyake et al. (2000)	83%	44%	40%	15%	9%	53%	48%	18%	11%
	Inhibition-Updating Merged	Klauer et al. (2010) - Study 1	44%	29%	28%	26%	23%	58%	58%	53%	46%
	Shifting-Updating Merged	Hedden & Yoon (2006)	62%	21%	17%	4%	2%	34%	28%	6%	3%
		Median	73%	34%	30%	14%	7%	56%	53%	15%	9%
		Mean	65%	38%	34%	14%	8%	52%	47%	22%	14%

Articles Excluded from Systematic Review Organized by Reason for Exclusion

1. **Did not involve a sample or sub-sample of cognitively healthy participants**

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2. **Did not report a confirmatory factor analysis of a multidimensional measurement**

model of executive function

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Supplementary Materials #2: Correlation Matrices from Re-Analysis

The Unity and Diversity of Executive Functions: A Systematic Review and Re-Analysis of

Latent Variable Studies

Correlation Matrices

Each of the following pages shows the list of variable names, means, standard deviations and an intertest correlation matrix. The variable names and construct assignments for each study are specified in the order of the correlation matrix (i.e., variable #3 corresponds to row/column #3 of the correlation matrix). For the data reported, means and specified in the top row, standard deviations are specified in the second row, and intertest correlations are specified in all subsequent rows. If the means and standard deviations were missing, they were replaced with 999.

Agostino et al. (2010)

Variable Order (Construct)

1. Mental-Attention Memory Task (M-capacity)
2. Direction Following Task (M-capacity)
3. Figural Intersection Task (M-capacity)
4. Antisaccade (Inhibition)
5. Color Stroop (Inhibition)
6. Number Stroop (Inhibition)
7. Letter Memory Task (Updating)
8. *n*-Back (Updating)
9. Trail Making Test (Shifting)
10. Contingency Naming Test (Shifting)

3.75 4.42 4.39 0.71 13.79 8.47 47.4 0.86 26.37 0.36
0.72 1.03 1.37 0.18 6.35 4.81 16.26 0.11 20.81 0.17
1
0.45 1
0.36 0.37 1
0.22 0.26 0.32 1
0.22 0.12 0.24 0.28 1
0.34 0.10 0.20 0.35 0.35 1
0.51 0.35 0.38 0.37 0.35 0.38 1
0.22 0.17 0.20 0.24 0.12 0.20 0.32 1
0.40 0.23 0.31 0.24 0.21 0.19 0.56 0.23 1
0.32 0.27 0.47 0.32 0.29 0.20 0.47 0.19 0.36 1

Arán-Filippetti (2013)

Variable Order (Construct)

1. Wechsler Intelligence Scale for Children, Fourth Edition (WISC-IV) Letter-Number Sequencing (Working Memory)
2. WISC-IV Digit Forward (Working Memory)
3. WISC-IV Digit Backwards (Working Memory)
4. Semantic Verbal Fluency (Cognitive Flexibility)
5. Phonological Verbal Fluency (Cognitive Flexibility)
6. Wisconsin Card Sorting Test – Complete Categories (Cognitive Flexibility)
7. Matching Familiarly Figures Test-20 – Total Errors (Inhibition)
8. Porteus Mazes (Inhibition)
9. Stroop (Inhibition)

```
999 999 999 999 999 999 999 999 999
999 999 999 999 999 999 999 999 999
1
0.69  1
0.73  0.62  1
0.44  0.28  0.37  1
0.58  0.47  0.51  0.62  1
0.65  0.57  0.57  0.27  0.41  1
0.64  0.53  0.56  0.35  0.49  0.57  1
0.65  0.54  0.56  0.29  0.41  0.59  0.66  1
0.40  0.32  0.38  0.28  0.35  0.32  0.31  0.33  1
```

Brydges et al. (2012)

Variable Order (Construct)

1. Stroop (Inhibition)
2. Go/no-go (Inhibition)
3. Compatibility reaction time (Inhibition)
4. Letter-number sequencing (Working memory)
5. Backward digit span (Working memory)
6. Sentence repetition (Working memory)
7. Wisconsin Card Sorting Test (Shifting)
8. Verbal fluency (Shifting)
9. Letter monitoring (Shifting)
10. Cattell Culture Fair Intelligence Test (Fluid intelligence)
11. Block design (Fluid intelligence)
12. Vocabulary (Crystallized intelligence)
13. Information (Crystallized intelligence)

```
999 999 999 999 999 999 999 999 999 999 999 999 999
999 999 999 999 999 999 999 999 999 999 999 999 999
1
0.03  1
0.13  0.06  1
0.32  -.03  0.17  1
0.26  0.13  0.07  0.36  1
0.14  0.03  0.06  0.36  0.22  1
0.23  0.05  0.13  0.38  0.20  0.17  1
0.39  0.02  0.18  0.40  0.31  0.29  0.22  1
0.29  -.01  0.20  0.40  0.28  0.13  0.28  0.26  1
0.29  0.03  0.19  0.48  0.31  0.24  0.41  0.38  0.43  1
0.37  -.04  0.18  0.45  0.32  0.32  0.39  0.41  0.42  0.59  1
0.28  -.10  0.12  0.45  0.25  0.63  0.31  0.40  0.30  0.40  0.52  1
0.28  -.10  0.14  0.56  0.35  0.52  0.32  0.48  0.36  0.45  0.52  0.79  1
```

de Frias et al. (2009) – Cognitively Elite Group

Variable Order (Construct)

1. Hayling (Inhibition)
2. Stroop (Inhibition)
3. Brixton (Shifting)
4. Color Trails (Shifting)
5. Reading Span (Working Memory)
6. Computational Span (Working Memory)

```
5.90   1.46   5.35   109.67   3.63   4.09
1.13   0.48   1.79   19.48     0.99   1.51
1
0.07  1
-0.15 0.09  1
0.19  0.12  0.07  1
0.06  0.22  0.04  0.19  1
0.06  0.14  0.11  0.29  0.52  1
```

de Frias et al. (2009) – Cognitively Normal Group

Variable Order (Construct)

1. Hayling (Inhibition)
2. Stroop (Inhibition)
3. Brixton (Shifting)
4. Color Trails (Shifting)
5. Reading Span (Working Memory)
6. Computational Span (Working Memory)

```
5.80  1.18  4.93  94.16     2.90  3.12
1.26  0.62  2.18  27.00     0.94  1.13
1
0.04  1
0.18  0.05  1
0.06  0.07  0.24  1
0.19  0.14  0.18  0.21  1
0.07  0.12  0.15  0.18  0.49  1
```

Duan et al. (2010)

Variable Order (Construct)

1. Digit 2-back (Updating)
2. Position 2-back (Updating)
3. Digit Go/Nogo (Inhibition)
4. Figure Go/Nogo (Inhibition)
5. Odd-More (Shifting)
6. Local-Global (Shifting)
7. Intelligence (Intelligence)

980.544	995.69	7.00	20.75	568.45	593.05	49.33
374.76	280.52	7.20	17.77	338.90	517.62	7.24
1						
0.748	1					
0.202	-0.146	1				
0.243	0.032	0.359	1			
0.647	0.525	0.216	0.343	1		
0.377	0.304	-0.064	0.141	0.481	1	
-0.548	-0.393	-0.343	-0.302	-0.337	-0.203	1

Fleming et al. (2016)

Variable Order (Construct)

1. Antisaccade (Inhibition)
2. Stop signal (Inhibition)
3. Stroop (Inhibition)
4. Keep track (Updating)
5. Letter memory (Updating)
6. Spatial 2-back (Updating)
7. Number-letter (Shifting)
8. Color-shape (Shifting)
9. Category switch (Shifting)

```
0.71  250   132   0.79  0.90  0.96  259   217   146
0.20  38    69    0.15  0.24  0.14  180   180   115
1
0.09  1
0.17  0.11  1
0.05  0.08  0.02  1
0.29  0.06  0.15  0.38  1
0.24  0.00  0.08  0.20  0.31  1
0.18  0.05  0.08  0.02  0.03  0.07  1
0.18  -.04  0.08  0.05  0.05  -.01  0.37  1
0.18  0.15  0.08  0.08  0.08  0.06  0.39  0.40  1
```

Friedman et al. (2011)

Variable Order (Construct)

1. Antisaccade (Inhibition)
2. Stop signal (Inhibition)
3. Stroop (Inhibition)
4. Keep track (Updating)
5. Letter memory (Updating)
6. Spatial 2-back (Updating)
7. Number-letter (Shifting)
8. Color-shape (Shifting)
9. Category switch (Shifting)
10. Wechsler Adult Intelligence Scale Intelligence Quotient (Intelligence)

```
1.04  282   214   0.94  1.09  1.17  331   331   333   102
0.20  63    90    0.18  0.25  0.17  183   189   181   11
1
0.26  1
0.16  0.14  1
0.18  0.23  0.21  1
0.25  0.16  0.25  0.46  1
0.21  0.24  0.12  0.27  0.26  1
0.14  0.26  0.23  0.13  0.19  0.15  1
0.16  0.22  0.27  0.14  0.14  0.12  0.41  1
0.21  0.28  0.25  0.17  0.16  0.19  0.48  0.43  1
0.23  0.22  0.26  0.54  0.43  0.30  0.05  0.09  0.17  1
```

Hedden & Yoon (2006)

Variable Order (Construct)

1. Plus-minus (Shifting)
2. WCST perseverative errors (Shifting)
3. Trail Making Test (Shifting)
4. Letter memory (Updating)
5. Backward digit span (Updating)
6. Self-ordered pointing (Updating)
7. Antisaccade (Prepotent Response Inhibition)
8. Stroop (Prepotent Response Inhibition)
9. Excluded letter fluency 1 (Resistance to Proactive Interference)
10. Excluded letter fluency 2 (Resistance to Proactive Interference)
11. Semantic fluency (Resistance to Proactive Interference)
12. Verbal paired associates – Immediate (Verbal Memory)
13. Verbal paired associates – Delayed (Verbal Memory)
14. Visual paired associates – Immediate (Visual Memory)
15. Visual paired associates – Delayed (Visual Memory)
16. Letter comparison 3 (Perceptual Speed)
17. Letter comparison 6 (Perceptual Speed)
18. Letter comparison 9 (Perceptual Speed)
19. List memory: Hits (List Memory)
20. List memory: False Alarms (List Memory)
21. List memory: Recollection (List Memory)
22. List memory: Familiarity (List Memory)

0.62 8.11 41.98 3.46 8.31 12.27 0.73 0.12 10.76 13.23 14.99 5.11 6.35 0.57 4.07 26.99 11.05 8.12 0.79 0.27 0.67 0.65

0.40 3.96 18.74 2.14 2.58 1.66 0.16 0.10 3.91 3.93 4.06 1.64 1.59 0.24 1.72 5.09 2.83 2.04 0.16 0.27 0.22 0.24

1

0.23 1

0.16 0.28 1

0.09 0.16 0.23 1

0.22 0.28 0.32 0.35 1

0.19 0.28 0.26 0.27 0.18 1

0.20 0.13 0.20 0.17 0.14 0.22 1

0.06 -0.07 0.21 -0.06 0.07 0.15 0.15 1

0.15 0.21 0.21 0.34 0.23 0.27 0.14 0.05 1

0.10 0.20 0.16 0.22 0.08 0.02 0.14 0.03 0.42 1

0.17 0.01 0.07 0.28 0.23 0.19 0.17 0.11 0.35 0.35 1

0.23 0.31 0.22 0.31 0.16 0.25 0.22 0.06 0.26 0.26 0.29 1

0.23 0.21 0.21 0.22 0.10 0.21 0.12 0.04 0.15 0.15 0.24 0.73 1

0.18 0.27 0.08 0.21 0.09 0.22 0.02 -0.1 0.11 0.12 0.31 0.47 0.49 1

0.22 0.25 0.11 0.22 0.09 0.28 0.09 -0.07 0.08 0.10 0.26 0.48 0.42 0.76 1

0.28 0.09 0.25 0.27 0.12 0.31 0.41 0.21 0.20 0.11 0.28 0.32 0.32 0.19 0.17 1

0.12 0.04 0.16 0.14 0.10 0.25 0.25 0.2   0.14 0.08 0.15 0.16 0.32 0.13 0.05 0.46 1

0.24 0.12 0.15 0.04 0.16 0.18 0.08 0.03 0.09 0.00 0.02 0.19 0.22 0.18 0.16 0.24 0.23 1

0.18 0.22 0.20 0.26 0.26 0.27 0.04 -0.12 0.22 0.23 0.31 0.36 0.33 0.43 0.35 0.15 0.14 0.14 1

-0.28 -0.13 -0.06 -0.16 -0.25 -0.10 -0.14 0.01 -0.16 -0.38 -0.23 -0.25 -0.16 -0.08 -0.12 -0.01 -0.04 -0.09 -0.46 1

0.27 0.12 0.22 0.18 0.32 0.24 0.20 0.00 0.29 0.27 0.38 0.35 0.36 0.14 0.19 0.11 0.08 0.19 0.65 -0.93 1

-0.10 -0.15 0.06 -0.03 -0.02 0.06 0.02 0.22 -0.10 -0.28 -0.05 0.00 0.08 -0.04 -0.06 0.12 0.16 -0.03 -0.24 0.56 -0.29 1

Hull et al. (2008)

Variable Order (Construct)

1. Local-global Verbal (Shifting)
2. Local-global Nonverbal (Shifting)
3. Plus-minus (Updating)
4. Keep-track Verbal (Updating)
5. Keep-track Nonverbal (Updating)
6. *N*-back Verbal (Updating)
7. *N* -back Nonverbal (Updating)
8. Stroop Verbal (Inhibition)
9. Stroop Nonverbal (Inhibition)
10. Antisaccade (Inhibition)
11. Tower of Hanoi (Complex executive function tasks)
12. Wisconsin Card Sorting Task (Complex executive function tasks)
13. Prosaccade (Validation tasks)
14. Vocabulary (Validation tasks)
15. Picture completion (Validation tasks)

```
202.22   217.12   41.02 6.55   11.28 13.7  24.11 243.68   63.22 0.28   87.67 6.56  0.04  52.28 21.70
167.20   166.05   10.07 5.67   8.41  9.37  12.82 102.69   60.91 0.15   24.48 4.66  0.02  7.87  2.85
1
0.49  1
0.07  -0.10 1
-0.22 -0.10 0.45  1
-0.14 0.06  0.30  0.42  1
-0.18 0.05  0.06  0.40  0.45  1
-0.05 -0.05 0.17  0.40  0.21  0.40  1
-0.14 -0.11 0.24  0.24  0.16  0.20  -0.03 1
-0.01 0.02  0.05  -0.06 0.19  0.16  -0.12 0.27  1
```

0.16 0.26 0.02 0.18 0.15 0.26 -0.22 0.13 0.09 1
-0.34 -0.05 -0.03 0.43 0.25 0.45 0.22 0.20 0.02 -0.01 1
-0.19 0.06 -0.01 0.36 0.36 0.39 0.19 0.30 0.00 0.24 0.43 1
-0.29 -0.25 0.09 0.32 0.58 0.33 -0.01 0.14 0.03 0.53 0.01 0.47 1
-0.04 -0.15 -0.27 -0.51 -0.42 -0.56 -0.35 -0.13 0.03 -0.22 -0.20 -0.37 -0.32 1
-0.07 -0.05 -0.23 -0.62 -0.52 -0.29 -0.15 -0.31 -0.11 -0.22 -0.34 -0.29 -0.32 0.36 1

Ito et al. (2015)

Variable Order (Construct)

1. Antisaccade (Response inhibition)
2. Stop-signal (Response inhibition)
3. Stroop (Response inhibition)
4. Keep-track (Updating)
5. Letter memory (Updating)
6. Spatial *n*-back (Updating)
7. Number-letter (Shifting)
8. Color-shape (Shifting)
9. Category-switch (Shifting)

```
61.98    247   141   73.32    75.12    80.73    243   241   156
14.36    32    70    8.60     13.49    6.80     156   160   119
1
0.16  1
0.18  0.09  1
0.19  0.03  0.17  1
0.32  0.02  0.30  0.37  1
0.39  0.04  0.14  0.31  0.38  1
0.18  0.11  0.23  0.07  0.12  0.11  1
0.07  0.00  0.12  0.02  0.06  0.06  0.37  1
0.25  0.10  0.16  0.08  0.12  0.11  0.50  0.41  1
```

Klauer et al. (2010) – Study 1

Variable Order (Construct)

1. Plus-minus (Switching)
2. Number-letter (Switching)
3. Colour-size (Switching)
4. Antisaccade (Inhibition)
5. Stop-signal (Inhibition)
6. Reading span (Working memory)
7. Operation Span (Working memory)

```
626   226   121   1.15  0.87  3.66  4.16
439   166   92    0.16  0.23  0.75  1.63
1
0.18  1
0.05  0.31  1
0.12  0.12  0.13  1
0.10  -0.04 0.17  0.26  1
0.03  0.08  0.05  0.21  0.27  1
-0.02 -0.02 0.05  0.11  -0.06 0.24  1
```

Klauer et al. (2010) – Study 2

Variable Order (Construct)

1. Semantic (Switching)
2. Number-letter (Switching)
3. Color-size (Switching)
4. Antisaccade (Inhibition)
5. Stroop (Inhibition)
6. Flanker (Inhibition)
7. Simon (Inhibition)
8. Reading span (Working memory)
9. Operation span (Working memory)
10. Counting span (Working memory)

```
172   232   134   83 135  58    29    9.87 9.54 11.75
108   123   94    40 1163 28    22    1.48 1.41 1.62
1
0.15  1
0.30  0.09  1
0.00  0.17  0.21  1
0.07  0.05  0.15  0.23  1
-0.16 0.00  -0.05 0.05  0.30  1
-0.01 0.12  0.12  0.25  0.17  0.21  1
-0.09 -0.12 -0.02 0.26  -0.10 0.04  0.13  1
-0.16 0.01  -0.06 0.22  -0.05 0.13  0.17  0.65  1
-0.04 0.01  0.04  0.22  -0.02 0.13  0.18  0.59  0.51  1
```

Lehto et al. (2003)

Variable Order (Construct)

1. Trail Making Test – Part A Time
2. Trail Making Test – Part B Time (Shifting)
3. Trail Making Test – Part C Time
4. Matching Familiar Figures, Time/First answer (Inhibition)
5. Matching Familiar Figures, Total errors
6. Auditory Attention and Response Set – Part A
7. Auditory Attention and Response Set – Part B (Working Memory)
8. Word Fluency (Shifting)
9. Mazes (Working Memory)
10. Spatial Span (Working Memory)
11. Spatial Working Memory, Between-search errors (Working Memory)
12. Spatial Working Memory, Strategy
13. Tower of London, Perfect solutions (Inhibition)
14. Tower of London, Additional moves

23   48.7 27.4 20.8 3.8   46.4 43.4 53.3 25.1 6.0   35.3 35.7 8.0   14.3
8.7   21.2 11.9 11.6 3.7   9.6   9.9   14   3.4   1.3   15.7 3.6   1.8   7.8
1
0.41   1
0.64   0.52   1
0.14   -0.11 0.13   1
-0.09 0.10   0.04   -0.51 1
-0.08 -0.05 0.07   0.06   -0.02 1
-0.05 -0.14 -0.02 0.13   -0.15 0.65   1
-0.12 -0.34 -0.27 0.22   -0.31 0.14   0.26   1
0.04   -0.20 -0.06 0.33   -0.36 0.25   0.36   0.25   1
-0.08 -0.22 -0.18 0.06   -0.06 0.18   0.20   0.25   0.31   1
0.08   0.18   0.13   -0.34 0.34   -0.24 -0.28 -0.27 -0.43 -0.36 1
0.05   0.17   0.13   -0.16 0.11   -0.13 -0.05 -0.23 -0.13 -0.16 0.61   1
-0.15 -0.26 -0.13 0.38   -0.37 0.08   0.20   0.27   0.29   0.16   -0.28 -0.11 1
0.18   0.36   0.22   -0.40 0.33   -0.09 -0.22 -0.39 -0.31 -0.24 0.31   0.12   -0.85 1

Miller et al. (2012)

Variable Order (Construct)

1. Backward Digit Span (Working Memory)
2. Backward Word Span (Working Memory)
3. Boxes hit ratio (Working Memory)
4. Preschool Continuous Performance Test – Omissions (Working Memory)
5. Preschool Continuous Performance Test – Comissions (Inhibition)
6. Preschool Continuous Performance Test – Hit ratio
7. Boy-Girl Stroop (Inhibition)
8. Tower of Hanoi (Inhibition)
9. Go/No-Go 1 – Comissions (Inhibition)
10. Go/No-Go 1 – Hit ratio
11. Go/No-Go 2 – Hit ratio (Set Shifting)
12. Go/No-Go 3 – Hit ratio (Set Shifting)
13. Dimensional Change Card Sort (Set Shifting)
14. Peabody Picture Vocabulary Test, Third edition – Raw score

```
0.81  1.14  0.73  7.80  6.24  0.79  15.86 0.07  2.39  0.75  0.74  0.79  12.15 67.87
1.14  1.25  0.13  6.39  7.67  0.18  3.46  0.04  2.03  0.22  0.20  0.20  4.15  18.24
1
0.78  1
0.23  0.24  1
0.38  0.50  0.19  1
0.20  0.26  0.09  0.28  1
0.29  0.35  0.13  0.58  0.9   1
0.12  0.26  0.19  0.15  0.24  0.24  1
0.18  0.18  0.15  0.20  0.30  0.35  0.09  1
0.13  0.15  0.15  0.24  0.39  0.42  0.31  0.17  1
0.23  0.31  0.15  0.37  0.23  0.33  0.20  0.19  0.43  1
0.30  0.41  0.12  0.48  0.34  0.47  0.28  0.17  0.18  0.22  1
0.18  0.22  0.10  0.29  0.17  0.27  0.16  0.28  0.14  0.27  0.25  1
0.45  0.59  0.19  0.44  0.09  0.22  0.19  0.13  0.19  0.40  0.40  0.26  1
0.46  0.48  0.18  0.29  0.35  0.39  0.22  0.29  0.30  0.36  0.33  0.26  0.53  1
```

Miyake et al. (2000)

Variable Order (Construct)

1. Plus-minus (Shifting)
2. Number-letter (Shifting)
2. Local-global (Shifting)
4. Keep track (Updating)
5. Tone monitoring (Updating)
6. Letter memory (Updating)
7. Antisaccade (Inhibition)
8. Stop-signal (Inhibition)
9. Stroop (Inhibition)
10. Wisconsin Card Sorting Test, Perseveration
11. Tower of Hanoi
12. Random Number Generation Component 1
13. Random Number Generation Component 2
14. Operation span
15. Dual task

15.5	546	210	0.63	0.70	0.99	1.16	0.78	166	32	46	0	0	43	0.89
10.8	250	160	0.14	0.26	0.13	0.16	0.29	60	12	12	1	1	6	0.13
1														
0.32	1													
0.23	0.32	1												
0.23	0.08	0.12	1											
0.22	0.19	0.00	0.15	1										
0.24	0.11	0.21	0.34	0.27	1									
0.15	0.17	0.11	0.12	0.26	0.22	1								
0.11	0.13	0.06	0.10	0.09	0.04	0.19	1							
0.07	0.09	-0.05	0.11	0.16	0.18	0.20	0.18	1						
0.26	0.13	0.18	0.09	0.19	0.14	0.15	-0.01	0.10	1					
0.08	0.10	-0.09	0.13	0.18	0.14	0.21	0.08	0.17	-0.02	1				
0.20	0.13	0.01	0.03	0.11	0.19	0.24	0.12	0.11	0.13	0.10	1			
0.20	-0.07	0.07	0.29	0.06	0.19	0.02	0.18	0.01	-0.08	0.12	0.02	1		
0.09	0.08	-0.04	0.41	0.28	0.34	0.16	0.13	0.20	0.16	0.04	0.17	0.13	1	
-0.03	-0.02	0.05	-0.09	-0.03	0.12	-0.08	-0.16	0.06	0.06	-0.18	-0.05	-0.09	-0.14	1

Rose et al. (2012)

Variable Order (Construct)

1. Spatial span (Working memory: storage)
2. Pattern span (Working memory: storage)
3. Change detection (Working memory: storage)
4. Spatial working memory (Working memory: storage and processing)
5. Counting span (Working memory: storage and processing)
6. Listening span (Working memory: storage and processing)
7. Go/no-go task – No-go trials (Inhibition)
8. Rapid visual processing (Inhibition)
9. Trail making (Shifting)
10. Intradimensional-extradimensional shift – Reversal trials (Shifting)

```
999   999   999   999   999   999   999   999   999   999
999   999   999   999   999   999   999   999   999   999
1
0.30  1
0.19  0.31  1
0.39  0.13  0.21  1
0.22  0.10  0.21  0.24  1
0.40  0.23  0.23  0.37  0.39  1
0.17  0.01  0.35  0.17  0.10  0.16  1
0.19  0.22  0.36  0.13  0.20  0.10  0.26  1
0.23  0.19  0.31  0.22  0.28  0.25  0.04  0.30  1
0.22  0.06  0.18  0.11  0.17  0.10  0.01  0.17  0.36  1
```

Usai et al. (2014)

Variable Order (Construct)

1. Circle Drawing Test (Inhibition)
2. Tower of London (Inhibition)
3. Dual Request Selective Task (Working Memory)
4. Backward Digit Span (Working Memory)
5. Semantic Fluency (Shifting)
6. Dimensional Change Sort Task (Shiftng)
7. Colored Progressive Matrices Test

```
0.55  22.98 4.63  2.04  27.91 0.86  17.68
0.23  4.35  2.71  0.59  6.49  0.25  3.39
1
0.252   1
0.182   0.158   1
0.146   0.327   0.245   1
-0.020  0.046   0.154   0.156   1
0.156   0.134   0.070   0.371   0.112   1
0.023   0.136   0.270   0.173   -0.029  0.095   1
```

Xu et al. (2013) – Ages 7 to 9

Variable Order (Construct)

1. 1back (Updating Working Memory)
2. 2back (Updating Working Memory)
3. Running Memory (Updating Working Memory)
4. Go/no-go (Inhibition)
5. Stroop (Inhibition)
6. Pinyins-digits (Shifting)
7. Dots-triangles (Shifting)

86.21 58.64 69.99 50.21 415.47   782.88   611.46
10.58 13.68 12.36 15.62 190.62   307.07   328.82
1
0.36 1
0.19 0.27 1
0.16 0.25 0.28 1
0.12 0.06 0.15 0.13 1
0.10 0.20 0.26 0.24 0.14 1
0.21 0.28 0.32 0.21 0.12 0.18 1

Xu et al. (2013) – Ages 10 to 12

Variable Order (Construct)

1. 1back (Updating Working Memory)
2. 2back (Updating Working Memory)
3. Running Memory (Updating Working Memory)
4. Go/no-go (Inhibition)
5. Stroop (Inhibition)
6. Pinyins-digits (Shifting)
7. Dots-triangles (Shifting)


```
91.12 66.3  80.9  58.42 309.48  722.03  591.55
6.36  13.83 10.21 18.06 185.82  284.28  284.37
1
0.30  1
0.15  0.36  1
0.17  0.21  0.14  1
0.19  0.24  0.20  0.14  1
0.25  0.29  0.23  0.19  0.19  1
0.14  0.11  0.15  0.23  0.04  0.11  1
```

Xu et al. (2013) – Ages 13 to 15

Variable Order (Construct)

1. 1back (Updating Working Memory)
2. 2back (Updating Working Memory)
3. Running Memory (Updating Working Memory)
4. Go/no-go (Inhibition)
5. Stroop (Inhibition)
6. Pinyins-digits (Shifting)
7. Dots-triangles (Shifting)

93.41 71.22 86.66 69.37 230.29   608.42   543.05
4.69   13.77 9.81 17.85 115.01   236.76   289.69
1
0.32   1
0.24   0.30   1
0.34   0.27   0.16   1
0.20   0.16   0.20   0.25   1
0.02   0.18   0.15   0.28   0.33   1
0.18   0.22   0.17   0.25   0.10   0.21   1