Clarifying inhibitory control: Diversity and development of attentional inhibition

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Abstract
Attentional inhibition is the ability to suppress task-irrelevant cognitive processing and ignore salient yet irrelevant features of the situation. However, it remains unclear whether inhibition is a singular function. Prominent are four proposals: a one-factor model of inhibition, an attentional model of inhibition, a response- versus cognitive-inhibition taxonomy, and an effortful- versus automatic-inhibition taxonomy. To evaluate these models, we administered nine inhibition and three attention tasks to 113 adults (Study 1) and 109 children (Study 2). Inhibition models were evaluated using confirmatory factor analysis after statistically controlling for attentional activation. Subsequent age analyses investigated whether inhibition tasks and factors related differentially to age, yielding distinct developmental trajectories. Results provide converging evidence for the automatic-effortful taxonomy - a distinction masked when the contribution of attention is ignored. These results highlight problems of isolated task-based characterizations of inhibition without a theoretical foundation based on evidence from multiple methodologies and populations.

Keywords
diversity, control, development, attentional, inhibitory, inhibition, clarifying

Disciplines
Education | Social and Behavioral Sciences

Publication Details

This journal article is available at Research Online: https://ro.uow.edu.au/sspapers/853
1. Introduction

Inhibition is important in normal and atypical development across the lifespan. In childhood, proficient inhibitory control is associated with an early literacy and numeracy advantage (Bull, Espy, & Wiebe, 2008; Clark, Pritchard, & Woodward, 2010; Espy et al., 2004), which is maintained through the early school years (Bull et al., 2008). In fact, inhibitory proficiency is implicated in children’s learning more generally (Bull et al., 2008), as well as emerging cognitive, behavioral, social, and emotional competencies (Garon, Bryson, & Smith, 2008; Riggs, Blair, & Greenberg, 2004; Riggs, Jahromi, Razza, Dillworth-Bart, & Mueller, 2006). Conversely, in older adults, inefficient inhibition interferes with memory retrieval, resisting distraction, and speed of processing (Hasher, Stoltzfus, Zacks, & Rypma, 1991; Hasher & Zacks, 1988). Further, deficient inhibitory control often is found in attention-deficit/hyperactivity disorder (Lijffijt, Kenemans, Verbaten, & van Engeland, 2005), schizophrenia (Bullen & Hemsley, 1987), autism (Ozonoff & Strayer, 1997), and obsessive-compulsive disorders (Enright & Beech, 1993).

However, there remains debate regarding development and construal (i.e., quantity, composition, and interpretation) of inhibitory function(s). Conceptual distinctions, suggesting fractionation of inhibitory processes, include: automatic inhibition (Johnson, Im-Bolter, & Pascual-Leone, 2003; Pritchard & Neumann, 2009), behavioural inhibition (Harnishfeger, 1995; Nigg, 2000); cognitive inhibition (Harnishfeger, 1995; Nigg, 2000), effortful inhibition (Johnson et al., 2003; Pritchard & Neumann, 2009), inhibition of return (Posner & Cohen, 1984), pre-potent inhibition (Ozonoff, Strayer, McMahon, & Filloux, 1994), resistance to proactive interference (Friedman & Miyake, 2004), and response inhibition (Verbruggen & Logan, 2008). There is similar diversity in proposed inhibitory functions, with inhibition suggested to apply in situations demanding: resistance to interference from distracting or competing stimuli; suppression of pre-potent responding/processing that impedes successful
performance; interruption of processes no longer task-relevant; or automatic deactivation of processes when controlled attention is applied elsewhere (Andres, Guerrini, Phillips, & Perfect, 2008; Collette, Germain, Hogge, & van der Linden, 2009; Friedman & Miyake, 2004; Miyake, Friedman, Emerson, Witzki, & Howarter, 2000; Nigg, 2000). Few studies have attempted to reconcile these conceptual distinctions, and fewer still present developmental data. As a result, currently there is no integrated model of inhibitory function.

1.1 Investigating the factor structure of inhibition

Prominent models of inhibition include one-factor (Cohen, Dunbar, & McClelland, 1990; Dempster, 1992; Diamond, 2006; Morton & Munakata, 2002) and two-factor accounts (Andres et al., 2008; Bjorklund & Harnishfeger, 1995; Collette et al., 2009; D’Amico & Passolunghi, 2009; Englehardt, Nigg, Ferreira, & Carr, 2008; Johnson et al., 2003; Pascual-Leone, 1984; Pritchard & Neumann, 2009). One-factor models propose a single inhibitory resource for interrupting task-irrelevant cognitive processes. Such models assume a single developmental trajectory of inhibitory control. In contrast, multi-factor accounts (described below) propose that multiple resources contribute to inhibitory function, resulting in diverging developmental trajectories and distinct relationships with other cognitive processes.

1.1.1 The TCO model of mental attention and attentional interruption

The Theory of Constructive Operators’ (TCO) model of mental attention distinguishes between *effortful* and *automatic* inhibition (Johnson et al., 2003; Pascual-Leone, 1984; for additional researchers drawing a similar distinction, see Andres et al., 2008; Collette et al., 2009; D’Amico & Passolunghi, 2009; Munakata et al., 2011; Pritchard & Neumann, 2009). According to the TCO, the most highly activated cluster of compatible schemes applies to determine performance. It is not always the case, however, that the most highly activated schemes are ideal. In *misleading situations*, such as those typical of inhibition tasks, schemes that are highly activated (due, e.g., to salience or over-learning) are often incompatible with
correct performance. Correct performance in these situations requires that task-relevant schemes be hyper-activated by way of effortful mental attention, while task-irrelevant schemes are concurrently inhibited (Pascual-Leone, 1984). Effortful inhibition thus entails the intentional suppression of task-incompatible mental operations. Pascual-Leone (1984) explains that as a by-product of this process, an automatic form of inhibition applies on schemes outside the focus of effortful mental attention (Arsalidou, Pascual-Leone, Johnson, Morris, & Taylor, 2013; Pascual-Leone, 1984). That is, automatic inhibition spontaneously and effortlessly deactivates mental operations outside the focus of controlled effortful attention, which occurs as a by-product of effortfully focussing on task-relevant schemes. This ensures that schemes within the focus of mental attention emerge as dominant for determining performance.

According to the TCO model, mental attentional energy (and with it effortful activation and effortful inhibition) increases with age along Piagetian sub-stages until about 15-16 years of age (Pascual-Leone & Johnson, 2005, 2011). In contrast, simple/automatic perceptual attention (involving mostly passive automatic attention and automatic inhibition) is controlled by the brain’s default network and reaches maturity by a much younger age. The TCO therefore posits two distinct forms of inhibition (effortful and automatic) that are predicted to follow distinct developmental trajectories. In support of this assertion, task-based research suggests that automatic inhibition develops earlier and more rapidly than effortful inhibition, reaching adult-like levels by 5 years of age (Ford, Keating, & Patel, 2004; Lechuga, Moreno, Pelegrina, Gomez-Ariza, & Bajo, 2006; Pritchard & Neumann, 2009). Additional findings support this distinction, including: (i) the neural network underlying automatic inhibition at least partially differs from that of effortful inhibition (Chambers et al., 2007; Lechuga et al., 2006; Steel et al., 2001); and (ii) children identified as intellectually precocious outperform their same-aged peers on tasks requiring effortful, but not automatic inhibition (Johnson et al.,
2003) – a dissociation also found in older adults (Collette et al., 2009) and in schizophrenics (Huddy et al., 2009; Ungar, Nestor, Niznikiewicz, Wible, & Kubicki, 2010).

1.1.2 A general limited-resource account of inhibition

General limited-resource models for endogenous activation of processes within cognitive development (e.g., Case, 1985), in contrast, posit a general-purpose pool of mental resources that is available for allocation to ongoing cognitive processing. This limited pool of resources is considered ‘general’ because it is not restricted to a specified mental function (the TCO, in contrast, proposes various specific resources – e.g., mental attention, automatic/perceptual attention, inhibition, etc. – whose functional interactions dynamically produce performance). Bjorklund and Harnishfeger’s (1990; Harnishfeger, 1995) extension of the general limited-resource model emphasizes the role of inhibition in the efficiency of cognitive processing. Specifically, increasingly efficient inhibitory control insulates against the activation of task-irrelevant information, thereby conserving the general (and capacity-limited) activatory resource for task-relevant processing. Harnishfeger (1995) distinguishes inhibitory processes by what they act upon. That is, behavioural inhibition involves effortful withholding of an overt behaviour/response that is highly automatized and thereby pre-potentiated, whereas cognitive inhibition entails internal suppression of distracting or otherwise task-irrelevant cognitive processing (see also Englehardt et al., 2008; Nigg, 2000).

Supporting this distinction, behavioural inhibition has been implicated in development of object permanence and self-regulation, whereas cognitive inhibition is believed to underlie developmental increases in ability to resist distraction and reorient attention (Harnishfeger, 1995). Further support for this dichotomy exists, including: (i) partial differentiation in brain activity with respect to inhibiting responses versus resolving cognitive conflicts (Chambers et al., 2007); and (ii) performance dissociations between tasks demanding suppression of motor responses versus resistance to distraction (Collette et al., 2009; Johnson et al., 2003). In
addition, studies with atypical populations (e.g., ADHD) suggest that associated cognitive deficits might be linked to response inhibition but not cognitive inhibition (Englehardt et al., 2008; Nigg, Butler, Huang-Pollock, & Henderson, 2002).

1.1.3 Attentional models of inhibition

Some researchers argue that apparent inhibition effects can be explained entirely in terms of attention, without distinct inhibition processes (Cohen et al., 1990; Kimberg & Farah, 1993; Morton & Munakata, 2002). Supported by computational modeling, this model posits that deficits in ‘inhibitory control’ reflect the strength of automatized latent biases (pre-potent responding or processing) outpacing available attentional resources. That is, rather than ‘inhibition’ being mobilized to suppress pre-potent responses, the controlled increase in attentional energy toward task-relevant processing overcomes these pre-potent biases. Against such interpretation, however, is neuropsychological evidence that patients with frontal lobe lesions are easily distracted, have difficulty ignoring salient irrelevant information, and have difficulty interrupting ongoing cognitive processing (e.g., Shallice, 1988) – deficits that are not easily accounted for by strictly attentional processing.

1.2 An investigation of the unity or diversity of inhibitory control

To investigate the unity or diversity of inhibitory function(s), Friedman and Miyake (2004) used confirmatory factor analysis and structural equation modeling, obtaining two distinct inhibition factors. The first factor corresponded to an ability to suppress pre-potent responses and resist interference from distraction. An unrelated second factor indexed the ability to resist intrusions from no-longer task-relevant information (‘resistance to proactive interference’). These findings thus support a response-distractor vs. proactive interference taxonomy, challenging conceptual (one- and two-factor) models of inhibition, including purely attentional accounts.

However, ten of the 11 models tested by Friedman and Miyake (2004) – consisting of all
possible combinations of three conceptual inhibition functions – provided similarly good fit to the data. In fact, models displaying good fit included one distinguishing automatic from effortful inhibition, as well as a one-factor model of inhibition. Although confirmatory factor analysis should be guided by both statistical and theoretical considerations to test a priori predictions, Friedman and Miyake’s (2004) final model selection was guided only by statistical results (e.g., correlation between latent factors, non-significantly better model fit). This lack of theoretical guidance is particularly problematic when selection among models is not based on significant differences in goodness of fit.

Further, the models assessed by Friedman and Miyake (2004) overlooked the contrast between controlled effortful attention (activation) and inhibition (deactivation) – a common oversight in the inhibition literature. This important relationship is highlighted by the TCO, and also by working memory theories positing controlled attention as a causal factor underlying individual differences in inhibitory processing (Redick, Heitz, & Engle, 2007). Neglecting this distinction leaves open the possibility that extracted latent constructs might reflect individual differences in domain-general capacities (e.g., attention, working memory), rather than the proposed inhibitory processes (Blair & Willoughby, 2013).

1.3 The current study

In light of these qualifications, we revised Friedman and Miyake’s (2004) methodology. Nine inhibition tasks were selected to evaluate four distinct models of inhibition, namely: a one-inhibition-factor model; an automatic vs. effortful (two-factor) inhibition model; a cognitive vs. response (two-factor) inhibition model; and a no-inhibition-factor model (i.e., an attentional-activation model of inhibitory function). To evaluate these models, three representative tasks indexed each of the following categories:

1. *Effortful response inhibition* – Effortful withholding of a highly automatized (pre-potent) response. This was indexed by a *Stroop task, stop-signal task, and antisaccade task,* each
requiring inhibition of a pre-potent response (for an alternate account of the Stroop effect, see Cohen et al., 1990).

2. **Effortful cognitive inhibition** – Effortful suppression of task-irrelevant cognition that was previously activated via controlled effortful attention, but is now unconducive to correct performance. This was indexed by a directed forgetting task, Hayling task, and proactive interference task, all requiring inhibition of a mental representation.

3. **Automatic cognitive inhibition** – Resisting interference from distracting information by applying controlled attention elsewhere (e.g., to task-relevant information). This was indexed by a negative priming task, retrieval-induced forgetting task, and flanker task, each involving suppression of non-target stimuli as a byproduct of focusing attention toward a target (for an alternate account of negative priming effects, see Neill, Valdes, Terry, & Gorfein, 1992).

Three tasks indexing effortful/mental attention served to statistically control for mental-attentional activation: running span task, counting span task, and figural intersections task. Although these tasks are often seen as testing working-memory capacity limits, effortful mental attention is acknowledged as their main organismic limiting factor (Cowan, 2005; Engle, Tuholski, Laughlin, & Conway, 1999; Pascual-Leone & Johnson, 2005). These tasks thus estimate the number of schemes that concurrently can be coordinated within mental attention. Inclusion of these measures provided three advantages: (i) an enhanced evaluation of one- vs. two-factor models of inhibition, by removing attentional-activation variance; (ii) control for general-intelligence abilities often mobilized in novel cognitive tasks (a shared variance carried by the effortful-attention activation factor; Blair & Willoughby, 2013); and (iii) the ability to evaluate an attentional account of inhibitory function.

The current study thus extends existing research in several ways: (1) models of inhibition were systematically contrasted using developmental data; (2) these contrasts were done after
controlling for mental attention; and (3) final model selection was made on both theoretical and statistical grounds. Under these conditions, when mental-attention variance is controlled, we expected the effortful vs. automatic model of inhibition to best fit the data.

3. Material and Methods

3.1 Participants

Participants were 115 students from two public schools in the Greater Toronto Area (child sample) and 120 undergraduates from a university research participant pool (adult sample). The child sample was drawn from a multicultural, middle-class area that is above the provincial average in employment rate and family income. The adult sample was drawn from a university student body that reflects the multicultural nature of Toronto and, as a publicly funded university, draws students from a range of socioeconomic levels. Data for six child and eight adult participants were lost due to early withdrawal. The final sample consisted of 29 grade 2 students (age range = 7.04 to 7.94 years; \( M = 7.54, SD = 0.27 \)), 34 grade 4 students (age range = 9.08 to 10.05 years; \( M = 9.55, SD = 0.51 \)), 46 grade 6 students (age range = 11.11 to 12.06 years; \( M = 11.55, SD = 0.27 \)), and 112 university students (age range = 17.85 to 51.41 years; \( M = 20.96, SD = 4.89 \)). Females comprised 55\% (\( n = 60 \)) of the final child sample (\( N = 109 \)) and 71\% (\( n = 80 \)) of the final adult sample.

3.2 Tasks

There were six measures of effortful inhibition (Stroop, antisaccade, stop-signal, Hayling, directed forgetting, and proactive interference) and three of automatic inhibition (flanker, negative priming, and retrieval-induced forgetting). These tasks also could be classified as indexing behavioural inhibition (antisaccade, Stroop, and stop-signal) or cognitive inhibition (Hayling, directed forgetting, proactive interference, flanker, negative priming, and retrieval-induced forgetting). Three measures of controlled, effortful attention served to remove shared attentional-activation variance from latent inhibition factor(s). For all inhibition tasks, lower
scores reflect more efficient inhibition. For all attention tasks, higher scores reflect greater mental attentional capacity. Three other tasks (i.e., Matrix Reasoning, Wisconsin card sorting, and letter memory tasks) were administered, but not incorporated into the inhibition models.

Unless otherwise specified, tasks were created with E-prime 2.0 software (Psychology Software Tools, Pittsburgh, PA) and run on a laptop computer. Task instructions and stimuli (e.g., words to be read and memorized) were verified as appropriate for the range of ages studied. For instance, words used for recall tasks (i.e., retrieval induced forgetting, proactive interference, and directed forgetting tasks) and expected sentence completions (i.e., Hayling task) were nouns derived from Battig and Montague’s (1969) category norms; they were selected on the basis of length (three to seven letters), non-inclusion in other tasks, and appropriateness for children as young as 7 years of age (identified by the Children’s Printed Word Database; Stuart, Masterson, Dixon, & Quinlan, 1996).

3.2.1 Automatic/cognitive inhibition measures

3.2.1.1 Negative priming task

This task (adapted from D’Amico & Passolunghi, 2009) consisted of eight training and 40 test prime-probe pairings, presented as follows: 500 ms fixation cross; prime trial presented until verbal onset; 500 ms blank screen; probe trial presented until verbal onset; 1000 ms blank screen. Stimuli for prime and probe trials consisted of two vertically arranged letters or numbers. One character of each pair was black and the other red. Participants had to quickly name aloud the red character (target) and ignore the black one (distractor). Trials were divided evenly between: (1) a negative priming condition, in which the target character for the probe trial had been the distractor in the prime trial; and (2) a baseline condition, in which all prime and probe characters differed. Trials with letter and number stimuli were evenly represented within each condition and were in the same random order for all participants. An external microphone connected to an E-prime serial response box recorded
auditory onset. Instances in which auditory onset was not an acceptable response (e.g.,
external sound, participants’ non-response utterances) were noted and excluded from analysis.
The negative priming effect was indexed by the difference between the median probe
response time for the baseline and negative priming conditions.

3.2.1.2 Flanker task

This task (adapted from Emmorey, Luk, Pyers, & Bialystok, 2008) was comprised of a
baseline condition with 12 trials, in which participants were shown a single red chevron; and
a test condition with 60 trials, in which participants were shown a red chevron flanked by four
black chevrons. The black flankers could be congruent or incongruent with the direction of
the red target. Congruent and incongruent trials were evenly, yet randomly selected. Baseline
was preceded by five practice trials, and test by 12 practice trials. Participants had to quickly
press the mouse button corresponding to the direction the red chevron pointed (left or right).
All trials began with a 250 ms fixation cross, followed by the stimulus until the earlier of a
response or 2,000 ms. Inhibition was indexed by the difference between incongruent and
congruent median response times for correct trials (Stins, van Baal, Polderman, Verhulst, &
Boomsma, 2004).

3.2.1.3 Retrieval-induced forgetting task

This task (adapted from experiment 1 in Williams & Zacks, 2001) began with
participants studying the exemplars in 60 category-exemplar pairs (10 categories with six
exemplars each) for later recall. Pairs were presented one at a time in random order, for 5000
ms each. Each pair was presented with a category name in capitals separated by a dash from
its lowercase exemplar (e.g., TOOL - hammer). The study condition was followed by a
practice condition, in which participants verbally completed prompted exemplar stems (e.g.,
TOOL-ha______). Practice items consisted of three exemplars from each of six categories (i.e.,
half the exemplars from 60% of the categories). This served to distinguish initially studied
exemplars as either: (a) practiced (e.g., TOOL - hammer); (b) non-practiced, but from practiced categories (e.g., TOOL - saw); or (c) non-practiced, from non-practiced categories (e.g., FRUIT - apple). Each practice item was displayed until the participant responded, after which the tester advanced the screen. Each practice exemplar stem was shown three times in random order; the full set of category-exemplar stems was presented before any stem was repeated. After a 15-minute retention interval (during which they completed the figural intersections task) participants were given a page listing the initially presented categories and were asked to write the initially studied exemplars from each category. Inhibitory control was indexed by the proportional decrease in recall for non-practiced items from non-practiced categories, calculated as \[
\frac{\text{proportion of (b) items recalled} - \text{proportion of (c) items recalled}}{\text{proportion of (c) items recalled}}
\].

3.2.2 Effortful/response inhibition measures

3.2.2.1 Stroop color-naming task

This paper-based task (adapted from Stroop, 1935) required the participant to name aloud the ink colors of strings of printed text. Text was printed using six ink colors (i.e., red, orange, yellow, blue, green, and purple, which also were the color words used). Participants received two practice and three test conditions, in the same order, each using a separate page. The first practice page displayed six congruent word-ink pairings (e.g., the word ‘red’ printed in red ink) to illustrate the colors used. The second practice page showed 12 incongruent word-ink pairings (e.g., the word ‘red’ printed in blue ink), to acquaint participants with the procedure of naming aloud the ink color, rather than the printed text. Practice sheets were repeated when errors were made. The third page (neutral baseline condition) displayed 60 non-color words printed in the various ink colors (e.g., ‘debate’ printed in red ink). The fourth page (incongruent condition) displayed 60 incongruent word-ink pairings, and the fifth page (non-word baseline condition) showed 60 strings of asterisks (i.e., ‘******’) printed in the various
ink colors. Test stimuli were displayed six per row across 10 rows. Task instructions emphasized both speed and accuracy. The tester used a stopwatch to measure total time to complete each test condition. As an index of inhibitory control, time in the non-word baseline condition was subtracted from time in the incongruent condition (errors were not analyzed due to a floor effect for all age groups).

3.2.2.2 Antisaccade task

In this task (adapted from Miyake et al., 2000) each trial consisted of: a central fixation point (‘+’) displayed for a randomly-determined time (1,500 to 3,500 ms); followed by a 50 ms blank screen; a 225 ms visual cue (small black square) on either the left or right side of the screen; a 100 ms target stimulus (an encased, gray arrow pointing up, left, or right) on the opposite side of the screen from the visual cue; and finally a mask. Participants were told to focus their attention on the fixation point and then, upon appearance of the visual cue, look to the opposite side of the screen. As a result of the rapid sequence of events, failure to inhibit a reflexive saccade to the visual cue would result in the participant being unable to identify the direction the target stimulus was pointing (indicated by pressing the ‘←’, ‘↑’, or ‘→’ laptop key). Twenty-two practice trials and 90 target trials were administered. The order of stimuli (arrow direction, left vs. right side of screen) was determined randomly for each subject. The score was the proportion of incorrect target identifications.

3.2.2.3 Stop-signal task

This task (adapted from Miyake et al., 2000) was created and run with Flash 7.0 software on a laptop computer. It consisted of a simple reaction time (baseline) condition and five blocks of the test condition. Participants had to rapidly identify the color of a circle, pressing the ‘F’ key if the circle was blue or the ‘J’ key if it was red. During test blocks, auditory “stop” signals told participants to refrain from responding to the current stimulus, and auditory “go” signals reminded them to respond. There were 48 trials in each test block. On
50% of trials there was no auditory prompt, requiring participants to respond. Stop and go signals each were presented for 25% of trials. Presentation of stop signals was dynamically calibrated so that participants could inhibit their response on only about 50% of trials. To accomplish this, successful inhibition on a stop-signal trial resulted in the ‘stop’ prompt occurring 50 ms later on the next stop trial; whereas unsuccessful inhibition resulted in the ‘stop’ prompt being presented 50 ms earlier. If participants slowed responding by more than 2.3 times their latency from the practice condition, the program automatically prompted them with an auditory “faster” signal. Inhibitory control was indexed by stop signal reaction time (SSRT), an estimate of time taken to inhibit a simple response (for SSRT formulae, see Ridderinkhoff, Band, & Logan, 1999).

3.2.3 Effortful/cognitive inhibition measures

3.2.3.1 Proactive interference task

In this task (adapted from experiment 2 in Bialystok & Feng, 2009) participants studied four consecutive lists of 10 words for subsequent recall. Word stimuli were high frequency exemplars (Battig & Montague, 1969) of clothes, animals, or body parts. The first three lists were words drawn from the same category, whereas the fourth list contained words from a different category. This was preceded by a practice list of 10 semantically related words that were unrelated to these categories. Each list was presented as follows: words were shown for 1,750 ms each in random order, and participants read each word aloud; 250 ms blank screen; presentation of a two-digit number, from which participants verbally counted backwards by ones for 16 seconds; a chime and then a blank screen indicating start of a 20-second interval, when participants recalled aloud as many of the preceding 10 words as possible. This was followed by a 2-second interval, the end of which signalled the start of the next list with a chime. Inhibitory control was indexed by intrusions from previously studied items as a proportion of total recall for the second and third test lists.
3.2.3.2 Directed forgetting task

This task (adapted from experiment 1A in Zacks, Radvansky, & Hasher, 1996) involved study and subsequent recall of two 24-word lists. Individual words were presented as follows: 500 ms fixation cross; study word for 5,000 ms; 1,000 ms “F” or “R”, which prompted participants to forget (F) or remember (R) the just-studied word. Each list was preceded by two practice words (one with a cue to remember, one with a cue to forget) to ensure participants understood the cues. Immediately following each list, participants recalled in writing the to-be-remembered words from the just-completed list. After a 20-minute retention interval (during which they performed the antisaccade and Stroop tasks) participants had to recall as many words as possible from both study lists (including to-be-forgotten words). Inhibitory control was indexed by intrusions of to-be-forgotten items as a proportion of total recall across both study lists.

3.2.3.3 Hayling task

In this task (adapted from Burgess & Shallice, 1996) participants heard sentences with the last word missing and responded verbally under three conditions. In the baseline condition (RT₁), they completed 10 sentences with an appropriate word. In the baseline inhibition condition (RT₂), they completed 10 sentences with a word entirely unrelated to the sentence. In the inhibition condition (RT₃) they completed again the 10 sentences heard in the first condition, although this time with a word entirely unrelated to the sentence. Sentences were selected from Bloom and Fischler’s (1980) sentence completion norms, on the basis of being completed by a particular word at least two-thirds of the time. Each condition was preceded by two practice sentences, after which feedback was provided if needed. Responses and response latencies were recorded by the E-prime program using an external microphone. If a participant’s response was too related to the sentence or had been repeated (e.g., using the same unrelated word for multiple sentence completions) they were asked to provide an
alternate response. A latency of 60 seconds was recorded for a trial if no response was given within one minute. Inhibitory control was indexed by a difference score representing the median latency attributable to inhibiting previously activated representations, calculated as 

\[ (RT_3 - RT_1) - (RT_2 - RT_1) \] .

3.2.4 Attention measures

3.2.4.1 Running span task

In this task (adapted from Cowan et al., 2005) 27 auditory strings of digits (1 to 9) were presented in random order at a rate of 4 digits per second (to prevent rehearsal). Lists ended unpredictably after 12 to 20 digits (occurring three times each in random order). Digits did not repeat within a rolling window of seven consecutive digits nor did they appear in correct numerical order. The end of each auditory digit string (e.g., “195384276913”) was signaled by a visual prompt, upon which participants keyed-in as many digits as possible from the end of the list, in the order of their presentation (e.g., “76913”). Individual digits were scored as correct if they were accurately identified in the correct position relative to the end of the list (e.g., a list ending “61943” with a response of “69143” would receive a score of 3). Controlled effortful attention was indexed by mean accuracy across trials.

3.2.4.2 Figural intersections task

In this paper-and-pen task (Pascual-Leone & Baillargeon, 1994; Pascual-Leone & Ijaz, 1989), participants had to locate the area of common intersection among two to eight overlapping shapes. There were 36 items of differing difficulty (ranging from class 2 to 8 items, where class corresponds to the number of overlapping shapes), presented in the same randomized order to all subjects. Each FIT booklet contained five items per class, with the exception of class 4 which had six items. Verbal instruction on eight simple practice items preceded the test. For each item, subjects first placed a dot in each of a set of discrete shapes on the right hand side of the page. They then placed a single dot in the area of common
intersection among those same shapes (although potentially differing in size and orientation), presented in an overlapping configuration on the left hand side of the page. Seven items included an “irrelevant” shape on the left that was not present on the right; irrelevant shapes were to be ignored when responding. Mental attentional capacity was indexed by the total number of correct items (excluding irrelevant items, in order to reduce the influence of inhibitory function).

3.2.4.3 Counting span task

This task (adapted from Kane, Hambrick, Tuholski, Wilhelm, Payne, & Engle, 2004) presented participants with arrays comprised of dark blue circles, dark blue squares, and light blue circles. On each screen, participants counted aloud the dark blue circles (targets) and remembered the total for later recall. Upon completion of the count (indicated by the subject repeating the total, e.g., “1, 2, 3, 3”), the tester advanced the screen to the next array (preceded by a 500 ms blank screen). After a random number of arrays (containing anywhere from three to nine targets and four to 14 non-targets), a cue (“???”) prompted participants to write the recalled totals from the set of arrays, in order of presentation. Arrays were presented in the same random order to all participants. Sets varied from two to six arrays, with each length presented three times for a total of 15 sets. Score for an item corresponded to the number of totals recorded in the correct relative position. For example, participants responding ‘6, 8’ after viewing arrays containing six, nine, and eight targets would receive a score of two – yet would receive a score of zero if this response were reversed. Controlled effortful attention was indexed by mean accuracy across items.

3.3 Procedure

For the adult sample, tasks were administered in the following order: Matrix Reasoning; directed forgetting; negative priming; antisaccade; directed forgetting recall; counting span (followed by a break); Stroop; retrieval-induced forgetting; figural intersections task;
retrieval-induced forgetting recall (followed by a break); Hayling; proactive interference; Wisconsin card sorting; stop-signal; running span; letter memory; and flanker. The three consecutive testing segments ran about 45 minutes each, separated by a 15-minute break. For the child sample, to maximize attention levels, sessions were administered on separate days in the following order: directed forgetting, negative priming, antisaccade, directed forgetting recall, counting span, Hayling (session 1); Matrix reasoning, Stroop, retrieval-induced forgetting, figural intersections, retrieval-induced forgetting recall (session 2); proactive interference, Wisconsin card sorting, stop-signal, running span, flanker (session 3). Each session also lasted about 45 minutes. Task order was selected to ensure that similarly characterized tasks were sufficiently separated, tasks requiring delayed-word recall did not immediately precede or follow those involving words, and each section was similar in length.

4. Results

4.1 Between-group (age) analyses of variance

Between-group analyses of variance used data from the entire sample (i.e., children and adults) to evaluate whether scores on automatic-inhibition tasks would reach adult-like levels earlier in development than scores on effortful-inhibition tasks.

4.1.1 Automatic/cognitive inhibition measures

ANOVA s on each of the automatic/cognitive inhibition measures showed that only the flanker task displayed a main effect for Age: Negative Priming, $F(3, 218) = 0.64, p = .590, \eta^2 = .01$; Flanker, $F(3, 218) = 10.17, p < .001, \eta^2 < .12$; Retrieval-Induced Forgetting, $F(3, 218) = 2.02, p = .112, \eta^2 = .03$. Post-hoc REGWQ analyses indicated that the Grade 2 group underperformed relative to the other groups on the flanker task. Results thus indicate that the child groups were typically performing at adult-like levels on automatic/cognitive tasks, even when indexed to baseline performance in subsequent ANOVAs (Table 1).

4.1.2 Effortful/response inhibition measures
In contrast, ANOVAs for each of the effortful/response inhibition measures displayed a main effect for Age: Stroop, $F(3, 215) = 39.27, p < .001, \eta^2 = .36$; Antisaccade, $F(3, 223) = 91.73, p < .001, \eta^2 = .56$; Stop-Signal, $F(3, 173) = 40.56, p < .001, \eta^2 = .42$. Post-hoc REGWQ analyses indicated that none of the child groups were performing at adult-like levels on these tasks, even when indexed to baseline performance (Table 1).

### 4.1.3 Effortful/Cognitive Inhibition Measures

ANOVA results for effortful/cognitive measures were less consistent, with only the directed forgetting task displaying a main effect for Age, $F(3, 232) = 6.72, p < .001, \eta^2 = .08$. Post-hoc REGWQ analyses indicated that Grade 6 and adults had a lower rate of intrusions from to-be-forgotten words than Grade 2. However, considered in the context of adults’ significantly higher recall, $F(3, 232) = 95.77, p < .001, \eta^2 = .56$, and recall accuracy, $F(3, 232) = 76.89, p < .001, \eta^2 = .50$, yet no significant difference in number of intrusions, $F(3, 232) = 1.17, p = .321, \eta^2 = .02$, this may indicate that adults displayed more effective recall (fewer intrusions despite a higher rate of recall; Table 1) when faced with task-irrelevant stimuli. Similarly, the non-significant result for the proactive interference task, $F(3, 219) = 0.60, p < .613, \eta^2 < .01$, should be interpreted in the context of: (1) a floor effect in rates of intrusion across the entire sample, such that nearly 70% of the data points were within the bottom 20% of the range of scores; and (2) adults’ significantly higher rate of recall on semantically-related lists, $F(3, 219) = 23.67, p < .001, \eta^2 = .25$ (Table 1). This suggests that adults may have been more successful at resisting interference from semantically related words (because accurate recall of even a single correct word reduces the availability of additional correct words, yet has no impact on the availability of incorrect words).

The non-significant result for the Hayling task, $F(3, 216) = 0.50, p = .682, \eta^2 < .01$, is qualified by the possibility that children and adults might have adopted different strategies to perform the task. That is, examination of responses indicated that children frequently used
items from around the room as completion words, whereas adults appeared to consider the sentences more fully (often completing each sentence with a nonsensical, yet grammatically compatible word). These different strategies are likely to have influenced subsequent response times, making between-group comparisons problematic. However, within-group comparisons (i.e., subsequent CFA analyses) appear less problematic due to the similarity in strategy use within groups.

4.1.4 Attention measures

As predicted, ANOVA results for the attention tasks (Table 1) indicated an Age effect for each of the measures: running span, $F(3, 218) = 17.63, p < .001, \eta^2 = .20$; FIT, $F(3, 219) = 59.47, p < .001, \eta^2 = .45$; counting span, $F(3, 217) = 43.52, p < .001, \eta^2 = .38$. Scores increased with age for each attention task. Each group differed from all others on the FIT. On running span and counting span, adults scored higher than all child groups, and Grade 2 scored lower than other groups, but Grades 4 and 6 did not differ.

Figure 1 displays a summary of developmental trends on all tasks. The mental attention tasks display a pattern of growth that closely approaches a 45-degree linear function. This pattern is consistent with that predicted and repeatedly found with measures of mental-attentional ($M$-) activation, across a range of content domains (e.g., Pascual-Leone & Baillargeon, 1994; Pascual-Leone & Johnson, 2011). This 45-degree growth pattern is predicted by the TCO on the assumption of a monotonic, equal-interval rate of growth, between age-stages, for the effortful attentional ($M$) resource. As expected, the effortful/response inhibition tasks also show protracted development across these age groups, due to the tasks’ strong misleadingness (requiring both $M$-activation and effortful inhibition). In contrast, the automatic/cognitive tasks show little to no gain with age, as expected, given their predicted reliance on a more automatic form of inhibition. The effortful/cognitive tasks also show less-pronounced development across age groups, likely because they can more
easily be overlearned (developmental trends for these tasks were thus less consistent).

4.2 Confirmatory factor analysis (CFA)

Additional data screening prior to CFA analyses indicated that 62 participants (17 adults, 45 children) had at least one missing data point due to equipment malfunction, experimenter error, data not meeting inclusion criteria, or early withdrawal from a task. Because exclusion of these participants would have resulted in a loss of 27% of the data, compared to only 3% of the data points being missing, maximum likelihood estimation was used to impute the missing data. An Expectation-Maximization algorithm using SPSS’ missing value analysis was used to impute missing data. Imputation did not alter the overall pattern of findings, but allowed for generation of fit (i.e., SRMR) and modification indices that require a complete dataset.

Prior to data imputation, task-specific steps also were taken to minimize the influence of extreme observations and ensure that only valid responses were included in analyses. Despite these steps, data from 21 participants were identified as multivariate outliers by Mahalanobis d² statistics ($p_1$ and $p_2 < .05$). In addition, Mardia’s statistic indicated that the dataset displayed significant multivariate kurtosis (adult sample kurtosis = 32.22; child sample kurtosis = 56.83). To correct for extreme data points and multivariate kurtosis in the data, the Satorra-Bentler rescaled $\chi^2$ was inspected for all models. Because there was minimal difference between the fit statistics and factor loadings between the original and SB-transformed models, only results for the original models are presented.

Confirmatory factor analysis (CFA) using AMOS’ maximum likelihood estimation was used to evaluate the absolute and relative fit of the inhibition models. Because these models were non-congeneric (indicators loaded on more than one factor), the variance of latent variables was fixed to 1 and factor loadings were left unconstrained for observed variables (Kline, 1998). In accordance with Hu and Bentler (1998), and similar to Friedman and Miyake (2004), absolute fit was examined using chi-square statistics and relative fit was
assessed with Bentler’s comparative fit index (CFI, with values > .90 suggested to indicate good model fit; Smith & McMillan, 2001), the standardized root-mean-square residual (SRMR, with values < .08 suggested to indicate good model fit; Hu & Bentler, 1998), the root mean square error of approximation (RMSEA, with values < .05 suggested to indicate good model fit; Browne & Cudeck, 1993), and Akaike’s information criterion (AIC, with comparatively lower values indicating better model fit).

Because previous studies of inhibition typically have not introduced measures to control for the influence of attention, adult and child models first were analyzed without controlling for activation. These models provided poor fit to the data on an absolute and descriptive basis (Table 2) and thus are not described further. A latent (mental-attention) activation factor was introduced in all subsequent CFA analyses. Given the evidence that inhibition may differ in structure as a function of age (e.g., Lee, Bull, & Ho, 2013), adult and child samples were analyzed separately before collapsing them for structural equation modeling.

4.2.1 Adult CFA Models

First examined was a model accounting for inhibition-task variance purely in terms of attentional activation (top half of Figure 2). Despite frequently large factor loadings (11 of 12 loadings were at least .20; Table 3), poor model fit suggested that a purely attentional account did not appropriately characterize the data (Table 2).

The one-inhibition-factor model (bottom half of Figure 2) provided better fit to the data (Table 2). Nearly all tasks loaded significantly on the activation factor, with only three tasks loading significantly on the inhibition factor (six of the nine inhibition tasks displayed factor loadings of at least .20 on the inhibition factor, suggesting the influence of sample size and model complexity on statistical significance; Table 3). Effortful inhibition (in all tasks except Hayling) appeared to be absorbed by the activation factor, whereas automatic inhibition was largely segregated to the inhibition factor. Despite good overall fit and the relative strength of
a number of the factor loadings, inconsistent explanatory value of the model (suggested by five of the nine inhibition tasks having an $R^2 \leq .15$) signaled that the factor structure was not optimally captured by a single inhibitory factor.

The automatic-effortful inhibition model (top half of Figure 3) also provided good fit to the data (Table 2). There was a slightly increased AIC statistic relative to the one-inhibition-factor model, however AIC calculations penalize models for increased complexity. Difference between these two models was not statistically significant, $\chi^2(1, N=112) = 0.26$. Despite lack of significance for all loadings on the inhibition factors (partially due to sample size and model complexity), six of nine inhibition tasks displayed factor loadings of at least .20 on the inhibition factors. As found in the one-factor model, squared multiple correlations indicated inconsistent explanatory value ($R^2 \leq .15$ for five of nine inhibition tasks). The pattern of factor loadings again indicated that effortful inhibition tasks (all except Hayling) loaded on both the latent activation and effortful inhibition factors. In contrast, automatic inhibition tasks loaded only on the latent automatic inhibition factor. This pattern, coupled with comparable fit to the one-inhibition-factor model, suggests that performance on effortful inhibition tasks was co-determined by both mental attention (activation) and effortful inhibition, whereas automatic inhibition remained a distinct factor.

The response-cognitive inhibition model (bottom half of Figure 3), displayed equally good fit to the data (Table 2). Difference from the one-inhibition-factor model was not statistically significant, $\chi^2(1, N=112) = 0.11$. Although seven of nine inhibition tasks had loadings of at least .20 on the inhibition factors (Table 3), only six of nine inhibition tasks had squared multiple correlations exceeding .15, thus limiting the model’s explanatory value.

4.2.2 Child CFA Models

Paralleling results of the adult models, the purely attentional model of inhibition provided poor fit to the data. Although seven of nine inhibition tasks displayed factor loadings of at
least .20 (Table 3), poor model fit and inconsistent explanatory value (with six of nine inhibition tasks displaying an $R^2 \leq .15$) suggested that a purely attentional account of inhibition failed to capture the entire range of inhibitory function in this sample (Table 2).

Initial analysis of the one-inhibition-factor model indicated a negative variance on an error term, which was subsequently fixed to zero (Dillon, Kumar, & Mulani, 1987). The resulting model provided good fit to the child data (Table 2). Five of nine inhibition tasks loaded significantly on the activation factor (with six inhibition tasks displaying loadings of at least .20; Table 3). However, only the stop-signal and retrieval-induced forgetting tasks loaded significantly on the inhibition factor (with seven of nine inhibition tasks displaying loadings of less than .20 on this factor). The activation factor largely absorbed the effortful/response and automatic/cognitive tasks, whereas the inhibition factor captured little shared variance. Further, the effortful/cognitive inhibition tasks displayed little shared variance with either latent factor. Thus, despite acceptable fit, the one-inhibition-factor model lacked clear explanatory value.

Initial analyses of automatic-effortful and response-cognitive models indicated negative variances on error terms; the offending variances were fixed to zero. Both two-factor models provided reasonably good fit to the data. This was qualified, however, by only one indicator loading significantly on each of the inhibition factors. As with the one-inhibition-factor model, the effortful/response and automatic/cognitive inhibition tasks were predominantly absorbed by the activation factor, whereas the effortful/cognitive tasks contributed little shared variability to the models. There was no statistically significant difference in fit between the one-inhibition-factor model and either the automatic-effortful, $\chi^2(1, N=109) = 1.14$, or the response-cognitive model, $\chi^2(1, N=109) = 1.43$.

4.2.3 Incorporating age into a structural equation model

CFA results show the activation factor absorbing much of the inhibition variance in the
child models. However, it may be the case that a strong non-inhibitory source of variance (e.g., developmental variance) was driving these models, making impossible the emergence of clear inhibition factors. As a final step, given evidence in support of the automatic-effortful distinction from the adult models and ANOVA age comparisons, participants’ age was incorporated into a full-sample (collapsing adult and child data) automatic-effortful model of inhibition. While the resulting model displayed excellent fit to data (Table 2), factor loadings for age on the latent variables were particularly interesting (Table 3). Age loaded significantly onto the activation and effortful (but not the automatic) inhibition factors. Despite a large age range in our sample, age was thus not an important factor to explain automatic inhibition.

5. Discussion

This study provides novel and converging lines of evidence supporting the TCO’s distinction between effortful and automatic inhibition. Supporting the TCO’s prediction of a need for mental attention to cope with misleading situations (such as those requiring inhibition), models without an attentional-activation factor provided poor fit to the data. Once this attentional variance factor was included, one- and two-inhibition-factor models fit the data equally well. Although mental attention appears to be critical for inhibition, explanations of inhibitory function entirely contingent on attentional processes are insufficient (evidenced by poor fit of the purely attentional model). These results are consistent with the TCO’s claim that performance in misleading situations (a characteristic of effortful inhibition tasks) is co-determined by effortful attention and effortful inhibition (Pascual-Leone, 1984). The link between activation and effortful inhibition also is consistent with Engle’s view that working memory capacity reflects controlled attention and inhibitory ability (Redick et al., 2007); however, this view does not explicitly include automatic inhibition.

Support for automatic inhibition as distinct from effortful inhibition was derived from adult CFA results. Indeed, although the one-inhibition-factor model displayed good fit to the
data, its patterns of factor loadings (and shared variance) indicated semantic equivalence to the automatic-effortful model of inhibition. When imposing extraction of only two factors (activation and inhibition), the strong mental-attentional activation factor absorbed the effortful inhibition tasks, showing their use of mental attention. In contrast, automatic inhibition tasks were segregated to a separate inhibition factor. Good fit of the automatic-effortful model of inhibition (despite statistical penalty for added complexity), and its pattern of loadings, further support the TCO’s process modeling of effortful mental attention and effortful versus automatic inhibition.

Although the response-cognitive model of inhibition had similarly good fit to the data, it is difficult to reconcile with the mounting evidence that supports the automatic- versus effortful-inhibition distinction. This most notably includes their divergent developmental trajectories (Ford et al., 2004; Lechuga et al., 2006; Pritchard & Neumann, 2009). In our data, performance on all automatic inhibition tasks displayed a similar developmental trend, with even the youngest age group (i.e., 7 years) performing at adult-like levels. In contrast, the typical developmental pattern on effortful inhibition tasks was one of protracted change, with performance improving gradually with age. In fact, even the oldest school-aged group (i.e., 12 years) typically did not display adult-like levels of performance on these tasks. This developmental pattern is consistent with the TCO and also with previous findings (Ford et al., 2004; Johnson et al., 2003; Lechuga et al., 2006; Pascual-Leone, 1984; Pritchard & Neumann, 2009).

Although CFA modeling of child data was less conclusive, a non-inhibitory source of variance (the joint developmental growth of mental-attentional resources) may have caused tasks of effortful-attentional activation and of effortful inhibition tasks to cluster on the activation factor. Another possibility is that executive functions may be undifferentiated in early childhood, becoming more distinct with increasing age (Lee et al., 2013). Although
there is evidence for a lack of differentiation between attention and inhibition in childhood (Davidson, Amso, Anderson, & Diamond, 2006; Wiebe, Espy, & Charak, 2008), much research also supports discriminability of these functions (Lee et al., 2013; Miller, Giesbrecht, Mueller, McInerney, & Kerns, 2012).

As a final step toward exploring these age relations, a full-sample structural equation model incorporating age was evaluated. Despite the potential for inflated correlations when collapsing across broadly different age groups, age failed to load significantly on automatic inhibition (although it loaded on effortful inhibition and activation factors). Given that latent inhibition factors were defined predominantly by one or two indices (with effortful inhibition tasks loading largely on the activation factor), further research may be needed to validate these relations with age.

Evidence in the current study for an automatic-effortful model of inhibition is in conflict with Friedman and Miyake’s (2004) findings, which showed superior fit when collapsing ‘prepotent response inhibition’ (i.e., antisaccade, Stroop, and stop-signal tasks, which we regard as effortful/response inhibition tasks) with ‘resistance to distractor interference’ tasks (i.e., flanker and flanker-like distraction tasks, which we regard as automatic/cognitive tasks). Friedman and Miyake’s findings thus imply that a one-inhibition-factor model should provide optimal fit for our data. However, as suggested in section 1.3, their conclusion may be a consequence of not including mental-attentional (or working memory) capacity tasks.

6. Limitations of this Study

Although this new and converging evidence is important, it must be interpreted in light of occasionally low and inconsistent factor loadings. One possible interpretation of this low-load tendency might be that task-based inhibition phenomena (e.g., negative priming effect, Stroop effect, retrieval-induced forgetting effect, flanker effect) fail to tap a common source of inhibitory variance (Dempster, 1992; Nigg, 2000). While this suggestion gains support from
correlational inconsistency among inhibition measures (Band, van der Molen, Overtoom, & Verbaten, 2000; Shilling, Chetwynd, & Rabbitt, 2002), the presence of significant factor loadings in this and previous studies (e.g., Friedman & Miyake, 2004; Miyake et al., 2000) supports the existence of common inhibitory variance.

Alternatively, it could be argued that low factor loadings were caused by unacceptable reliability of the inhibition tasks adopted (Mueller, Kerns, & Konkin, 2012). Inability to calculate reliability estimates for a number of the tasks in the current battery (due to indices with a single score) might thus be seen as problematic for our conclusions. However, indirect evidence suggests that our results are not attributable to low reliability. Specifically, most of our tasks (except Hayling and retrieval-induced forgetting tasks) show significant inter-task correlations (Table 4). Further, squared multiple correlations, roughly interpretable as the reliability of a measure relative to its associated latent construct, suggest that current indices are sufficiently reliable measures of the latent construct (with all except proactive interference and negative priming exceeding an $R^2$ of .15 in one of the models).

Another possibility is that low factor loadings reflect small but meaningful relationships among inhibition measures (as evidenced by their consistently low correlations in this and previous studies; e.g., Friedman & Miyake, 2004; Miyake et al., 2000). For example, a meaningful relationship between Stroop and antisaccade tasks is evident in their significant correlation for our child and adult samples, even though neither task loads highly on the effortful inhibition factor. This ‘small but meaningful’ hypothesis becomes increasingly plausible when considering converging lines of evidence (good model fit, task-based developmental trends, diverging developmental trajectories), which consistently point toward an automatic-effortful model of inhibition.

Nevertheless, inconsistent factor loadings and issues of reliability highlight the need for further development and validation of inhibition measures (a sentiment echoed by Friedman
& Miyake, 2004). In future research, choice of inhibition tasks should be informed by process-analytical appraisal via process/task analysis to maximize congruency and relevance of tasks’ process formulas. That is, inhibition tasks with congruent task-process formulas should provide the best statistical results. We have task analyses for our mental-attention measures and for antisaccade, but lack them for other inhibition tasks taken from the literature. This is because our main research goal has been a different one – to compare inhibition tasks that are widely used in the literature.

Despite evidence for distinct developmental trends across diverse (automatic or effortful) inhibition tasks, there were three notable exceptions. First, performance on Hayling and proactive interference tasks (although classified as effortful inhibition tasks) appeared to reach adult-like levels by Grade 2 (7-8 years) – perhaps because children used different strategies. Indeed, adults appeared to consider incomplete sentences more fully before generating grammatically correct but nonsensical responses (an inhibition-intensive strategy). In contrast, children tended to name visually available objects or random nonsense words – often derived (and occasionally verbalized) in advance of sentence completion (a less inhibition-intensive strategy).

Similarly, even the youngest age group displayed adult-like performance in the proactive interference task. It is thus possible that proactive interference represents a distinct form of inhibitory processing (Friedman & Miyake, 2004); this interpretation is consistent with the relative lack of correlation between proactive interference and other inhibition tasks in the child and adult samples (Table 4). Alternatively, the relatively low rate of recall among the child groups (and consequently the low rate of intrusions) may have created a floor effect, restricting the range of children’s proportional intrusion scores. In contrast, adults showed significantly enhanced recall (providing increased opportunity for intrusions), but showed a non-significantly lower rate of intrusions (despite each word correctly recalled reducing the
proportion of correct responses remaining). A similar line of reasoning might be applicable to adults’ non-significantly lower rate of intrusions on the directed forgetting task.

7. Conclusions

The current study provides explicit concurrent evaluation of competing theoretical models of inhibition. We demonstrated the crucial role of mental attention in performance on inhibition tasks. Further, in extending investigation to a broader range of tasks and ages, we provide various novel and converging lines of evidence that support the distinction between automatic and effortful inhibition. A distinct automatic form of inhibition (that occurs as a by-product of effortful attending to task-relevant information; Johnson et al., 2003) was found to appear earlier developmentally than a more effortful form of inhibition. This finding agrees with past research (Ford et al., 2004; Lechuga et al., 2006; Pritchard & Neumann, 2009). However, previous accounts attempted to explain task-based findings without addressing causal mechanisms that might underlie distinct inhibition processes; that is, they neglected the critical role of mental attention and its development for empowering effortful inhibition. In contrast, the TCO has a theoretical account explaining both interaction and development of the two forms of attention (effortful/mental versus automatic/perceptual) and how these interact with inhibitory processing (Johnson et al., 2003; Pascual-Leone, 1984).

The current study has both methodological and theoretical implications. It calls for use of broad/organismic theoretical approaches (instead of extrapolating theory from single task-based effects) and encourages use of multiple measures, methods, and populations to identify converging lines of evidence. In addition, this and similar studies (e.g., Friedman & Miyake, 2004; Miyake et al., 2000) support the inhibition construct, suggesting it as a cause of shared variance among these tasks – variance that is not fully explained by attentional activation or inhibition alone. A more complete explanation of inhibitory function should look at the role of non-inhibitory factors (such as participants’ individual-difference processing formulas,
motivation, and intelligence) that may contribute to performance on inhibition measures.
Acknowledgements

This research was funded by standard research grant 410-2006-2325 from the Social Sciences and Humanities Research Council of Canada. We thank Carolyn Hagan, Katie MacDonald, Patricia Azarkam, David Sidhu, Navid Hejazifar, and Victoria Pillegi for assistance with data collection. Also Cathy Labrish and Dr. Rob Cribbie for help with CFA modeling. This paper is based on Steven Howard’s doctoral dissertation. Aspects of this research were presented at the 2013 Society for Research in Child Development meetings.
References


Blair, C., & Willoughby, M. (2013). Rethinking executive functions: Commentary on “The contribution of executive function and social understanding to preschoolers’ letter and


doi:10.1037/a0014168


Table 1

Descriptive Statistics and ANOVA Summary of Non-Imputed Data, by Group

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Note. NP=negative priming (NPDiff: median baseline RT - median NP RT; NPProp: proportional increase in median RT on NP relative to baseline trials); Flank=flanker (FlankDiff: median incongruent RT - median congruent RT; FlankProp: proportional increase in median RT on incongruent relative to congruent trials); RIF=retrieval-induced forgetting (RIFPropDiff: difference in the proportion of NINC and NIPC items recalled; RIFPropDecr: proportional decrease in recall for NIPC over NINC items; NINC = non-practiced items from non-practiced categories; NIPC = non-practiced items from practiced categories); Stroop (StroopDiff: difference in median Stroop and non-word baseline RTs; StroopProp: proportional increase in median RT on Stroop relative to non-word baseline trials); Anti=antisaccade (proportion of incorrect target identifications); SS=stop signal (estimated stopping time on stop trials); PI=proactive interference (PIProp: intrusions as a proportion of recall; PI: number of items recalled on lists with semantic interference); DF=directed forgetting (DF: intrusions as a proportion of recall; DFRec: number of accurately recalled words); Hay=Hayling (difference in median RTs associated with the prior activation of sentence completions); RS=running span (mean number of digits recalled in correct position); FIT=figural intersections task (total number of items correct); CS=counting span (mean array counts recalled in correct position). An asterisk denotes indices entered into CFA and SEM models.
Table 2

**CFA and SEM Model Fit Indices (Adult and Child)**

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*Note.* General rules of thumb to interpret model fit indices include: lower $\chi^2$ is better; RMSEA < .05 indicates good model fit; CFI > .90 indicates good model fit; lower AIC is better; and, SRMR < .08 indicates good model fit. *$p < .05$. 
Table 3

Factor Loadings for CFA Models

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Note. All factor loadings are standardized regression weights. Stroop, SS, Flank, PI, Hay and DF are scored in reverse to the other tasks (such that for these tasks lower scores indicate better inhibition). NP = negative priming; Flank = Flanker; RIF = retrieval-induced forgetting; Anti = antisaccade; SS = stop-signal; PI = proactive interference; DF = directed forgetting; Hay = Hayling; RS = running span; FIT = figural intersections task; CS = counting span. Significant paths have been bolded.
### Table 4

**Inhibition and Attention Task Correlations, by Sample**

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**Note.** Full correlations among inhibition and attention tasks for adult sample (top right) and child sample (bottom left) using the original, non-imputed data. Age = chronological age (in years); FIT = figural intersections task (total number of items correct); CS = counting span (total number of sums recalled in their correct position); RS = running span (total number of digits recalled in their correct position); NP = negative priming (median baseline RT - median NP RT); RIF = retrieval-induced forgetting (proportional decrease in recall for NIPC over NINC items); Flank = flanker (median incongruent RT - median congruent RT); Anti = antisaccade (proportion of incorrect target identifications); Stroop = Stroop (difference in median RT between Stroop and non-word baseline conditions); SS = stop signal (estimated stopping time on stop trials); PIProp = proactive interference (intrusions as a proportion of recall); DF = directed forgetting (number of intrusions from to-be-forgotten items on immediate recall tests); Hay = difference in median RTs associated with the prior activation of sentence completions). *p < .05.
Figure Caption

Figure 1. Illustration of developmental trends characterizing each task type. To more clearly highlight the different developmental trajectories, individual indices were converted to z-scores and then artificially dispersed by adding a different constant to each task type (e.g., all mental attention tasks had a constant of 3.5 added to the mean z-score for each age group). As a result, lines are directly comparable only to other tasks of the same task type. Of particular interest here is the overall shape and slope of the lines.

Figure 2. Adult confirmatory factor analysis model representing an attentional account of inhibitory function (top) and a one-inhibition-factor account of inhibitory function (bottom).

Figure 3. Adult confirmatory factor analysis model representing an automatic-effortful account of inhibition function (top) and a response-cognitive account of inhibitory function (bottom).