Cognition in Context: Validating Group-Based
Executive Function Assessments in Young Children

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Abstract

The current study describes and validates a set of group-based executive function (EF) assessments for use with young children. These situational tasks involve instructing groups of young students to march to music while completing tasks that place demands on their EF abilities. These efforts were motivated by providing researchers with a set measures that assess EF subcomponents while also accounting for the dynamic social processes present in group settings. These assessments take place in schools, are relatively simple to administer, and include multiple EF indicators. Drawing on a diverse sample of 283 Kindergarten students ($M_{\text{age}} = 5.8$ years; $SD = 0.38$ years), we found that group-based EF assessments were significantly related to individually-assessed EF measures, and differentially predicted children's performance on standardized tests of math and reading achievement. Overall, this study represents a first step towards developing a set of group-based EF measures that are appropriate for use with young children.

Keywords

Executive Function, Early Childhood, Group-Based Assessments

Executive function (EF) represents a complex set of cognitive skills involved in the control and regulation of important frontal lobe functions such as inhibition, working memory, and cognitive flexibility (e.g., Miyake, et al., 2000; Rothbart & Posner, 1985). These skills work in tandem to guide thoughts and behaviors by facilitating planning, problem solving, and enabling purposeful goal-pursuits (Zelazo, 2015). While work into the nature and development of EF is rooted in neuropsychological and cognitive research, EF has become a major focus in educational and developmental literatures over the past two decades, given its role in supporting early learning and school readiness (e.g., Carlson, Zelazo, & Faja, 2013; Blair, 2002). Despite the recent integration of cognitive science theories and tools into educational research settings, the use of standardized neurocognitive measures continues to dominate the applied EF literature (e.g., Weintraub et al., 2013; Zelazo, Blair, Willoughby, 2016).

Standardized EF tasks are designed to measure the cognitive processes underlying specific EF components, capturing differences in children's reaction time and accuracy rates in response to experimental stimuli (e.g., Weintraub et al., 2013; Zelazo et al., 2014). These tasks are typically administered to individual children in relatively quiet spaces one-on-one with a trained experimenter. Although there are many benefits of the experimental precision afforded by these highly controlled, laboratory-based measures, it is unclear the degree to which direct assessments reflect the complexities of employing EF skills in early classroom settings. Early learning environments tend to exert demands on children's ability to initiate behaviors, stay on-task, and monitor performance – often in the presence distractors, challenges and competing social and behavioral options – all of which direct EF tasks are not designed to assess (Silver, 2014; McCoy, 2019).

In the current study, we put forward a new set of tasks designed to capture behaviors

related to EF while children engage in activities like those they might encounter in typical early classroom settings. These situational tasks involve instructing groups of young students to march to music while completing tasks that place demands on their EF abilities, and were designed to capture behaviors related to three inter-related EF constructs: inhibitory control, working memory, and attention control. However, since these tasks require children to engage in activities in the presence of peers, they can also provide information on how EF skills might be employed in socially demanding settings like those encountered in the early schooling context.

Defining Executive Function

Although conceptualizations vary, EF is generally defined as a broad set of higher-order cognitive skills required to purposefully guide thoughts and behaviors to achieve goals (Carlson, Zelazo, & Faja, 2013). These skills enable individuals to exert control over basic cognitive processing and attention skills to flexibly adapt to dynamic environmental conditions (Miyake et al., 2000; Posner & Rothbart, 2000; Zelazo, 2015). EF is most commonly conceptualized as consisting of three distinct, yet related cognitive processes: inhibition, working memory, and cognitive flexibility (e.g., Blair and Diamond 2008; Diamond 2013). Inhibition includes both inhibitory control – or the ability to deliberately suppress pre-potent, automatic and impulsive responses to environmental stimuli – and attention control (also referred to as interference control or attentional inhibition), which is the ability to ignore distractions and to deliberately focus attention on stimuli of interest (Diamond 2013; Posner & DiGirolamo, 1998). Working memory is the ability to store, manipulate and recall multiple facets of information, while simultaneously updating and accessing mental memory representations (Baddeley, 2003; Miyake et al., 2000). The third core EF component is cognitive flexibility, which is sometimes referred to as set shifting or attention switching (Miyake et al., 2000). Cognitive flexibility is the ability to

adapt to changing demands or priorities and involves shifting back and forth between multiple tasks, operations, or mental sets (Diamond 2013; Monsell, 1996; Miyake et al., 2000). Each EF component is considered to be distinguishable, but they typically work together to enable planning and problem solving during deliberate goal-pursuits (Zelazo, 2015). EF is also considered to be related to, but distinct from, emotion regulation skills that require the management of affect and motivation (e.g., Zelazo & Carlson 2012).

EF development is protracted into adulthood, however, there has been particular interest in early EF development given its relevance for school readiness and early academic achievement. This is especially true during the transition into formal schooling, a period characterized by rapid developmental changes in EF skills (e.g., Best, Miller, & Naglieri, 2011; Shing, Lindenberger, Diamond, Lee, & Davidson, 2010; Wiebe, Sheffield, & Espy, 2012; Willoughby et al. 2012). The transition into school also marks a time when children begin to encounter growing demands associated with structured activities and formal learning and are asked to exhibit more EF and self-control (Pianta & Rimm-Kaufman, 2006). For young students, this means having to wait their turn to engage in activities, raise their hands before speaking, and resist becoming distracted by peers (Rimm-Kaufman, Curby, Grimm, Nathanson, & Brock, 2009).

Measuring Young Children's EF

Historically, researchers across academic disciplines have largely relied on three main modes of data collection when studying EF during early childhood: direct cognitive assessments administered one-on-one to individual children, naturalistic classroom observations, and indirect teacher or parent reports. Among the most commonly used are direct child assessments, adapted from standardized tasks developed by cognitive psychologists and neuroscientists (e.g., the

National Institutes of Health Toolbox for the Assessments of Neurological and Behavioral Functions; Bauer & Zelazo, 2014). Many of these measures are designed to have high conceptual precision, which allows researchers to isolate and study EF sub-components with relatively high levels of accuracy (Gershon et al., 2010). Many have also been rigorously evaluated using modern psychometric approaches, demonstrate high construct validity and longitudinal stability over time, and have been normed across a wide age-range using culturally and geographically diverse samples (e.g. Bauer & Zelazo, 2014; Zelazo et al., 2014). A critical feature of direct EF assessments includes the context in which they are administered. Specifically, these tasks are designed to be administered to individual children in relatively quiet spaces in order to minimize distractions and optimize task performance (e.g. Weintraub et al., 2013). While this approach is intended to allow researchers to measure children's cognitive capacity, the experimental control that is a core feature of these tasks limits the extent to which they measure how children employ these skills in "real-world" settings where they encounter natural distractions and competing social and behavioral options (McCoy, 2019; Silver, 2014).

Conversely, observational methods can offer a way to study children's EF skills as they manifest in a classroom or early care environment. Two commonly used approaches to observing children's EF in classrooms include behavioral coding of video-recorded activity during classroom instruction and real-time independent assessments of children's behavior during an activity, task, or instructional practice (McCoy, Jones et al., 2017; Moffitt & Morrison, 2019). While these observational techniques have the power to capture children in their natural environment, their sensitivity to the specific phenomena of interest can be eroded by lack of experimental control inherent to the real-world. Because researchers can only passively observe what is happening in the classroom setting, it is often not possible to elicit specific behaviors of

interest or to differentially study separate EF components. Further, despite having high levels of ecological validity, observational approaches to studying children's EF are relatively new, less commonly used, and their psychometric properties have not been well studied or evaluated (e.g., McCoy, 2019).

The third major EF measurement approach involves asking teachers, caregivers, and/or parents to rate how well children employ EF and related skills in typical environments, such as classrooms or home settings. There are various advantages to using adult ratings to assess children's EF skills. First, compared to direct assessments and observational approaches, rating scales provide researchers with an efficient, practical, and low-cost option for measuring children's EF skills (McCoy, 2019). Rating scales significantly reduce testing time, resources, and are simple to administer. Second, teacher and parent report measures allows raters to consider how children employ EF across different settings, generating a general profile of children's EF skills, as opposed to snapshots of performance on laboratory-based tasks in controlled settings (McCoy, 2019). Relatedly, rating scales are typically considered more ecologically sensitive than individually assessed cognitive tasks, as they can provide information and capture processes that are relevant to real-world behaviors and outcomes. Despite these benefits, rater reports can also place a substantial burden on raters who complete these scales and evidence suggests can be susceptible to bias (e.g., Beaman, Wheldall, & Kemp, 2006; Garcia, Sulik, & Obradovic, 2019). Further, raters might have difficulty teasing apart EF skills from academic, social, temperamental, and other behavioral constructs distinct from EF (Abikoff et al., 1993; Duckworth & Yeager, 2015; McCoy, 2019). Issues of low precision and high subjectivity of rater reports can potentially limit their utility in studying early EF development. In fact, recent studies have yielded weak relations between different raters' reports on the same

child using the same scale (McCoy, 2019; Sullivan, & Riccio, 2007), and studies demonstrating low convergence between adult ratings and direct assessments suggest that these two EF measurement approaches might tap into distinct constructs (Clark, Pritchard, & Woodward, 2010; Mcauley et al., 2010; Toplak, West, & Stanovich, 2013).

Contextual Effects on Children's Executive Function

Research into classroom peer effects on young children's EF performance has been steadily accumulating over the past decade. Findings from this work suggest that having classmates with poor self-regulation and EF skills can negatively influence the acquisition and development of individual EF skill development during elementary school (Finch et al., 2019; Montroy, Bowles, & Skibbe, 2016; Weiland, Ulvestad, Sachs, & Yoshikawa, 2013). Much of this research has leveraged multi-level modeling techniques to estimate peer effects by generating classroom averages of students' performance on standardized EF tasks – consistently finding links between average peer EF skills and individual students' EF performance across early schooling (Finch et al., 2019; Montroy, Bowles, & Skibbe, 2016; Weiland, Ulvestad, Sachs, & Yoshikawa, 2013). Recently, researchers have also employed novel group-based administration procedures to evaluate the effects of peers on children's EF performance. For example, Obradović and colleagues (2018) administered neurocognitive EF tasks on tablet computers to entire classrooms of 3rd-5th grade students to complete simultaneously. Findings from this study revealed differential performance on each EF task when administered individually versus in a classroom setting, providing additional evidence that a group context (i.e., classroom) can influence an individual's EF performance (Obradović, Sulik, Finch, Tirado-Srtayer, 2018). While innovative administration procedures and advanced statistical analyses have provided some evidence of this phenomenon, these studies rely on lab assessments not

designed to reflect the complexities of deploying EF skills while engaging in group-based activities. Importantly, children did not have the opportunity to interact with one another as they typically would when employing EF skills in naturalistic settings.

One example of interactive, group-based EF measures in the literature include the situational assessments designed by McCabe and Brooks-Gunn (2007), in which young children engage with same-age peers to complete tasks design to measure behavioral self-control. These situational assessments were administered to individual children, as well as to groups of five, same-age peers. Results revealed that children scored lower on these tasks when in the context of peers than when assessed individually, suggesting that although children might be able to optimally self-regulate individually, their performance can be hindered in the presence of peers and distractions (McCabe & Brooks-Gunn, 2007). Despite the innovation of these situational tasks and the information they provide about the importance of considering context when studying children's behavior, they were primarily designed to capture children's ability to delay gratification and are quite narrow in scope. Other key aspects of children's EF abilities can be studied using this methodological framework and can shed light onto the social influences exerted on children's cognitive processes.

Current Study

Given the success of situational tasks to assess skills like delay of gratification (McCabe & Brooks-Gunn, 2007), similar approaches could yield insight into the cognitive features of self-regulation. In this study, we test the feasibility of administering group-based EF assessments to young students in a school setting. These tasks were designed to capture behaviors related to three inter-related EF constructs: inhibitory control, working memory, and attention control while children are in groups. Here we describe the administration and coding procedures and

carry out psychometric tests to validate a new set of tasks designed to measure EF-related behaviors while children engage in activities like those they might encounter in typical early classroom settings.

First, we examined the factor structure to assess the construct validity and dimensionality of the group-based EF measures. Next, we tested concurrent validity by comparing our group-based assessments with well-established laboratory EF tasks that measure similar cognitive constructs (i.e., inhibitory control, working memory, and attention control). We predicted that children's performance on the group-based assessments would be significantly and strongly related to analogous lab-based tasks. Third, we examined predictive validity of each group-based measure of EF. We expected that children's performance on group-based EF assessments would be significantly related to standardized tests of math and reading achievement and expected that these associations would be robust to demographic covariates. Based on prior research (Ahmed, Tang, Waters, & Davis-Kean, 2019; Nguyen, & Duncan, 2019), we hypothesized that measures of working memory would emerge as the strongest predictor of math and reading achievement, and that all EF components would be more strongly related to early math than to reading achievement (e.g., Bull and Scerif, 2001).

Method

Sample

Participants were 283 kindergarteners (149 boys, 134 girls) from seven elementary schools (26 classrooms) in Southeastern Michigan. The seven schools in the study included populations of students from diverse SES and racial/ethnic backgrounds. Percentage of students eligible for free or reduced-price lunch at the school level were 2%, 33%, 39%, 42%, 61%, 69% and 72%. Forty-two percent of children attending the sampled schools were White, 33 % were

Black, 17 % Asian, 2 % native American/Alaskan native, and 6 % more than one race. Children's age at testing ranged from 4.99 to 6.98 years old ($M = 5.8$ years, $SD = 0.38$).

Procedure

Prior to testing, parents and teachers provided informed consent, and children provided verbal assent prior to task administration. Each child was assessed by trained research assistants using a battery of individually-assessed EF tasks and standardized tests of math and reading achievement in quiet, unused classrooms or multipurpose room in schools. Individually-assessed EF tasks and standardized tests of math and reading achievement were administered to children consecutively on the same day during each visit to children's schools. The order in which these tasks were administered was counterbalanced using a two-block design to reduce the possibility of fatigue or other ordering factors influencing the results. On a subsequent visit (on average two weeks after academic and behavioral testing), a battery of group-based EF assessments were administered to groups of children in unused classrooms or multipurpose room in schools. Experimental groups were formed based on a random draw of all consented children within each school that participated in the current study. These tasks were administered using the same order, starting with the Freeze Task, followed by the Jumping Task, and finally the Marching Task (see measures section below for a description of each task). This research was carried out in accordance with ethical standards at [Blinded] Institutional Review Board (HUM00085500), ["Blinded"].

Group-based Tasks

Adapted and modified from teacher-administered challenge tasks (Lan, 2009; later adapted by Berhenke, 2013), the group assessments are a set of three tasks designed to measure behaviors related to EF performance in a group setting. Across all three tasks, researchers

instruct a small group ($M = 4.8$; $SD = .81$) of kindergarten students to continually march in a circle, and to carry out various actions prompted by musical cues. Performance on these tasks was scored using accuracy indicators and reaction times. Four main indicators were present across the tasks; stop times, distractibility markers, and recall and performance codes. The stop time indicators present in all three group-based tasks represent children's ability to suppress behavioral responses, or in this case, their ability to inhibit the urge to continue walking when the music begins or stops playing. Like lab tasks of inhibitory control, these indicators measure how well a child can inhibit automatic behavioral urges. We also coded how distracted a child became while completing each task (i.e., distractibility), as a measure of attention control, and the degree to which children could remember multistep instructions and carry out the correct number of operations in the instructed sequence as an index of working memory (i.e., action recall and action performance). Administration protocols can be found in Appendix B.

Coding

All tasks were administered and video-taped by trained research assistants, and behavioral coding was conducted to assess children's EF skills within each task. Behavioral coding of the group-based tasks was conducted using the ELAN computer software (ELAN Version 5.8). This open source tool allows for manual and semi-automatic annotation and transcription of audio or video recording, and supports multi-level, multi-participant annotation of time-based media. Inter-rater reliability was obtained from video recordings in the laboratory. Six coders were involved in the coding of the participants. First, a random sample of 20% of the videos were coded by the project manager. Then, each additional coder (undergraduate and graduate student researchers) recoded this sample to assess reliability before independently coding. Coders were given a 100 milliseconds margin of error for stop-time trials across all three

tasks (e.g., 783ms vs 700ms was considered reliable for a particular trial), and were required to achieve at-least 80% absolute agreement across all tasks before independently coding (Cohen, 1960; Hallgren, 2012). Additional coding details can be found in Appendix A.

Freeze Task

During the Freeze Task, researchers instructed the group of students to continually march in a circle, and to immediately freeze like a statue when music began playing. When the music stopped playing, children were instructed to continue marching. Children were told that they can only unfreeze themselves when the researcher said “unfreeze” or when the music stopped again. One practice trial was conducted to ensure children understood the instructions. This task was repeated for five trials. A separate experimenter controlled the music and started and stopped it at random intervals (7-15 seconds in length), using a stopwatch (see testing protocol in Appendix A). The length of music varied randomly to avoid practice effects across trials. This was done to ensure there were no systematic differences across trials, tasks, or groups. Reliability among scores obtained by different experimenters ranged from 87%-98% Overall average reliability was 94%. Behavioral coding of the Freeze Task consisted of children’s stop times and distractibility.

Stop-Time is the speed with which children stopped marching when the music began playing, coded in milliseconds, with larger values indicating poorer performance. Inter-rater reliability among coders was 87%.

Distractibility is the degree to which children became distracted or engaged in behavior that interfered with their task performance, coded on a Likert scale, with larger values indicating better performance. Specifically, children that were observed as having multiple occurrences of distractions and/or disruptive actions and verbalizations were assigned a score of 0; a score of 1

indicated some occurrences of distractions initiated by self; a score of 2 indicated some occurrences of distractions initiated by peers; and a score of 3 indicated no instances of distractions or interference (i.e., body and face are directed at the experimenter, attentive expression, no disruptive actions or verbalizations). Specific behaviors associated with distractibility can be found in Appendix A: Group-Based Executive Function Assessments Coding Scheme. Inter-rater reliability among coders was 98%.

Jumping Task

During the Jumping Task, the group of students were told to march in a circle while music was playing, and to immediately freeze like a statue when the music stopped. In this task, however, participants were also given one-to-three additional instructions to complete when the music ended. For the one-step instruction, participants were instructed to jump three times after freezing like a statue. After the one-step instruction trial, the researcher provided participants with two-step instructions (“jump three times and clap twice”), and three-step instructions (“jump three times, clap twice, and crouch down”). Thus, when children marched, they had to also remember the instructions for what to do once the music ended. One practice trial was conducted to ensure children understood the instructions. This task was repeated for three trials. Like the Freeze tasks, a separate experimenter controlled the music and started and stopped it at random intervals (7-15 seconds in length), using a stopwatch (see testing protocol in Appendix A). Reliability among scores obtained by different experimenters ranged from 82%-97%. Overall average reliability was 92%. Behavioral coding of the Jumping Task consisted of children’s stop times, distractibility, action recall and action performance.

Stop-Time is the speed with which children stopped marching when the music ended, coded in milliseconds, with larger values indicating poorer performance. Inter-rater reliability among coders was 82%.

Distractibility during the Jumping task was measured using a Likert scale in the same way described for the Freeze Task. Inter-rater reliability among coders was 94%.

Action Recall is the children's ability to correctly follow the one-through-three step instructions, scored on a Likert scale, with larger values indicating better performance. Specifically, children who did not respond or produced irrelevant or completely incorrect responses were given a score of 0; a score of 1 was assigned to children who performed actions incorrectly after learning (visually or verbally) from a peer; a score of 2 was assigned to children who performed the actions incorrectly without being cued by a peer; a score of 3 was assigned to children who performed the actions correctly after learning (visually, verbally) from a peer; and a score of 4 was assigned to children who performed the actions correctly without learning the actions from a peer. Children's performance was scored per action for each trial, such that the maximum score for trial 1 (one-step instruction) was 4; the maximum score for trial 2 (two-step instruction) was 8, and the maximum score for trial 3 (three-step instruction) was 12. Trial performance was summed across all three trials to indicate total performance accuracy within the task. Inter-rater reliability among coders was 96%.

Action Performance is the accuracy with which children carried out the one-through-three step instructions. Each time a child performed fewer actions than instructed (e.g., jumps twice when instructed to jump three times), performed more actions than instructed (e.g., jumps twice when instructed to jump once), or performed different actions than instructed (e.g., claps when instructed to jump) they were assigned a score of 1 (for each deviation from the given

instructions). This was repeated across each trial and across all step instructions. A zero therefore indicated perfect performance, whereas the higher the score, the less accurate the performance. Children's performance was scored per action for each trial and summed across all three trials to indicate total performance accuracy within the task. Inter-rater reliability among coders was 97%.

Marching Task

During the Marching Task, the group of students were told stand in a circle, facing the center. They were instructed to march in one direction if one song began playing (left for song 1) and the opposite direction if a second song began to play (right for song 2). Children were instructed to immediately freeze like a statue, when the song stopped, and to turn back and face the center of the circle before starting the next trial. Two practice trials were conducted to ensure children understood each instruction. This task was repeated for seven trials. Like the Freeze and Jumping tasks, a separate experimenter controlled the music and started and stopped it at random intervals (7-15 seconds in length), using a stopwatch (see testing protocol in Appendix A). Reliability among scores obtained by different experimenters ranged from 70%-97%. Overall average reliability was 87%. Behavioral coding of the Marching Task consisted of children's stop times, distractibility, march recall and march performance.

Stop-Time is the speed with which children stopped marching when the music ended, coded in milliseconds, with larger values indicating poorer performance. Inter-rater reliability among coders was 70%.

Distractibility during the Marching task was measured using a Likert scale in the same way described for the Freeze Task. Inter-rater reliability among coders was 87%.

March Performance is the degree to which children correctly marched in the appropriate direction; scored on a Likert scale: 0 (incorrect); 1 (self-corrected); and 2 (correct). Inter-rater reliability among coders was 97%.

March Recall is the degree to which children were visually or verbally cued by a peer, scored as a dichotomous variable: 0 (cued); and 1 (not cued). Inter-rater reliability among coders was 93%.

Individually Assessed Tasks:

Inhibitory Control. The **Head-Toes-Knees-Shoulders (HTKS)** task (Ponitz et al., 2008) was used to measure children's inhibitory control. In this task, the child was asked to perform opposite movements of the directions instructed. For example, when asked to touch their head, children were expected to touch their toes. The task became increasingly challenging across 30 trials, separated into three blocks (block 1: touching heads and toes; block 2: touching knees and shoulders; and block 3: a mix of the two). Incorrect responses were scored with a 0, 1 for a self-corrected response, and 2 for a correct response. The maximum total score was 60. The internal consistency in the current study sample (Cronbach's α) is .83. Reliability among overall scores obtained by different experimenters was 100%.

Working Memory. The **Backward Digit Span** subtest of the Wechsler scales (Wechsler, 1991) was administered to measure children's working memory capacity, as the task requires the manipulation of information stored in short-term memory. This task was composed of two sections in which the instructor said a list of numbers and the participant was asked to recite the numbers in reverse-order. The list of numbers increases by one item for every correct response. If the participant answered incorrectly twice in a row, the instructor moved onto the next section. This measure demonstrates acceptable test-retest reliability ($r = .73$; Lipsey et al., 2017).

Attention Control. The **Pair Cancellation** task, which is a measure drawn from the Woodcock-Johnson III Tests of Cognitive Abilities (Woodcock & Mather, 2000), was used to test children's attention control. In this task, children were presented with a testing sheet filled with rows of small pictures of dogs, balls, and cups, and asked to circle all of the ball-dog pairs where a dog is presented after a ball. After practicing to ensure that the child understood the task, each child was given three minutes to complete the full task, working as quickly as they could without making mistakes. There were a total 69 correct pairs, and the number of correct pairs identified within three minutes was recorded. Test-retest reliability from external validation is $r = .78$ (Woodcock, McGrew, & Mather, 2001).

Academic Achievement: Math and reading skills were measured using the Applied Problems and Letter-Word Identification subtests from the Woodcock-Johnson III Tests of Achievement (Woodcock, McGrew, & Mather, 2001). The Applied Problems subtest assessed early math skills using word problems, pictures and numbers. Participants were asked to listen to the item, determine the procedure to solve the problem and successfully complete the computations. The task grew increasingly difficult and the participants were given a pencil and paper after they reached a certain point in the task to help solve the problems. The Letter-Word Identification subtest assessed children's early reading ability. Children were asked to identify and read letters and words with proper pronunciation. The task grew increasingly difficult as the participant progressed. Due to lack of item-level data, we were unable to calculate internal consistency of this measure. However, external validation efforts have demonstrated excellent reliability (Cronbach's $\alpha = .93$) for the academic achievement battery among kindergarten students and very high test-retest reliability ($r = .95$; Woodcock, McGrew, & Mather, 2001).

Demographic Variables: Children's demographic characteristics, such as age and sex, were obtained from consent forms signed by participants' parents. Eligibility for free or reduced-price school lunch was obtained at the school-level across all 7 participating elementary schools.

Statistical Methods

Descriptive analyses were conducted using IBM SPSS Statistics version 26 (IBM Corp. Armonk, N.Y., USA). Confirmatory factor analysis and structural equation modeling were carried out using Mplus version 8.5 (Muthén & Muthén, 1998–2017). Measures with negative valance (all stop-time indicators and Jumping Task action performance) were reverse-coded to aid in interpretability. Given the non-normal distributions of the Jumping Task indicators (see Table 1), we fit our factor analytic and structural equation models using MLR estimation, which provides maximum likelihood parameter estimates with robust standard errors (Asparouhov, & Muthén, 2015). Stop time indicators were converted from milliseconds to seconds to align their variances with other study indicators, allowing convergence in our multivariate models (Muthén, 2010). Finally, due to the nested structure of the group-based EF data, standard errors were adjusted to account for clustering around the experimental groups using the TYPE=COMPLEX command in Mplus (Muthén & Muthén, 1998–2017).

We used a four-step procedure to validate the newly-developed group-based EF tasks. First, confirmatory factor analysis (CFA) was used to evaluate the dimensionality of each EF task. We compared the fit of models with different configurations of our variables of interest based on prior research. The best-fitting model was then chosen using the appropriate fit statistics. We evaluated Comparative Fit Index (CFI), which compares the fit of a target model to the fit of an independent, or null, model, and Tucker Lewis Index (TLI), sometimes referred to as Normed Fit Index (NFI), with values between 0.95 and 1.00 indicating good model fit (Kline,

2005; Hu & Bentler, 1999). We also examined the Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR), which is the difference between the residuals of the sample covariance matrix and the hypothesized model, with values less than .08 and .06, respectively, indicating good model fit (Browne & Cudeck, 1993; Hu & Bentler, 1999). Finally, we compared the relative fit of our models using the scaled Satorra-Bentler scaled chi-square difference test, which accounts for the scaling correction factor necessary for robust estimation (Satorra, & Bentler, 2001; Yuan-Bentler, 2000).

We hypothesized that a three-factor solution would best fit the data. We chose to load specific indicators onto their respective latent variables based on the type of skill required to carry out the sub-measures across task. Since each task (e.g., Jumping Task) required children to employ more than one EF skill, we chose to base our latent variables using similar indicators across task rather than use each task as a separate latent variable. Specifically, we expected that a child's ability to inhibit the urge to continue walking when the music begins or stops playing (i.e., stop times) across all three tasks would constitute an inhibitory control latent variable, the distractibility codes across all three tasks to constitute a separate latent variable of attention control, and action performance and action recall of the Jumping Task would constitute a working memory latent variable, as these indicators require children to remember multistep instructions and carry out the correct number of steps in the instructed order. We also tested the model fit of a unitary factor structure consisting of all group-based indicators, as well as a 2-factor structure consisting of all of the stop times and distractibility scores (i.e., inhibitory control and attention control indicators) loaded on one factor and the action performance and action recall of the Jumping Task (i.e., working memory) onto a separate factor. March Recall and March Performance indicators from the Marching Task were not included in our measurement or

structural models for two reasons. First, although March Recall and March Performance required children to pay attention to which song was playing and to march accordingly (left for song 1 and right for song 2), these two indicators index different aspects of attention than the distractibility indicators used to make up the attention control factor. Further, when administering and coding these tasks, it became apparent that children found these two features of the marching task difficult to understand. In combination with the very low observed correlations between March Recall and March Performance and the other model indicators (see table 2.), we chose to omit these two indicators from the measurement and structural models of the current study.

Second, we examined bivariate correlations to assess the direction and magnitude of associations among group-based EF latent variables, lab EF tasks, and tests of academic achievement. Third, tests of concurrent validity of the group-based EF latent variable(s) were tested using structural equation modeling. Each lab-based EF component was regressed on all three group-based EF latent variables simultaneously to examine unique associations between each group and lab-based EF component. We chose to use HTKS as an analogous measure for the inhibitory control latent variable consisting of stop time indicators, as both require children to inhibit pre-potent responses to external stimuli (one in the presence of peers and the other individually), Pair Cancellation to map onto the attention control latent variable consisting of distractibility indicators, and Backward Digit Span as the analog to the group-based working memory latent variable, as both of these measures required children to retain, manipulate and recall information.

Finally, in a separate structural equation model, we examined the predictive validity of each group-based EF latent variable by testing relations to standardized tests of math and reading

achievement. In this model, sex, age at group-task testing, percent of children eligible for free or reduced-price lunch, group size, and proportion of boys in each group were entered as covariates.

Missing Data

The full sample included 283 kindergarten students, however, there was a small amount of unplanned missingness across the main study variables due to student absences or testing schedule conflicts. Further, descriptive statistics revealed that one data point for the Freeze Task Distractibility indicator was out of range due to a data entry error and was subsequently declared as missing. Missing data across the EF and achievement variables ranged from 0.4% to 11.7% (see Table 2 for sample size for each study variable). Moreover, the TYPE=COMPLEX command in Mplus was used to account for clustering around the experimental groups, which resulted in a final analytic sample size of 252 children, nested across 55 experimental groups (i.e., maximum N of group-based indicators). Little's missing completely at random test (MCAR; Little, 1988) was conducted to examine missing data mechanisms in the current sample. Results from Little's MCAR test produced a non-significant chi-square value ($\chi^2 (156) = 176.23, p = .128$), suggesting that data in the currently sample are missing randomly (Little, 1988). Full Information Maximum Likelihood (FIML; Arbuckle, 1996) estimation was employed. Unlike listwise deletion, which can yield biased estimates (Enders, 2001), FIML leverages all available data to estimate study parameters and standard errors and is considered effective in achieving unbiased regression estimates in the presence of data missing at random (Schafer & Graham, 2002).

Results

Descriptive Statistics

Means, standard deviations, sample sizes, ranges, and coefficients of skewness and kurtosis for all unstandardized model indicators are presented in Table 1. Pearson's bivariate correlations for main study indicators are presented in Table 2.

Factor Solution of the Group-Based EF Assessments

Both the unitary ($\chi^2(20) = 232.8, p < .001$; CFI = .46; TLI = .25; RMSEA = .21; SRMR = .11) and 2-factor models exhibited poor model fit ($\chi^2(19) = 290.3, p < .001$; CFI = .31; TLI = .00; RMSEA = .24; SRMR = .08). The three-factor solution consisting of inhibitory control, working memory and attention control latent variables demonstrated acceptable model fit ($\chi^2(17) = 43.2, p < .001$; CFI = .93; TLI = .89; RMSEA = .08; SRMR = .05). As is evident in Figure 1, standardized factor loadings for each latent factor in our 3-factor model were significant and exceeded a cutoff value of 0.40 (Stevens, 1992). CFI, TLI, RMSEA and SRMR goodness-of-fit indices of the 3-factor solution all met or exceeded the appropriate values for our determination of acceptable model fit. Further, results from the Satorra-Bentler scaled chi-square difference test (Satorra, & Bentler, 2001) revealed significant differences ($\chi^2(1) = 7.9563, p = 0.005$) between the chi-square statistic of the unitary ($\chi^2(20) = 232.80$, scaling correction factor = 1.1383) vs. the 2-factor model ($\chi^2(19) = 290.32$, scaling correction factor = .6027) as well as significant differences ($\chi^2(3) = 222.31, p < 0.001$) between the chi-square statistic of the unitary ($\chi^2(20) = 232.80$, scaling correction factor = 1.1383) compared to the 3-factor structure solution ($\chi^2(17) = 43.20$, scaling correction factor = 1.1689).

Associations Among Group EF Latent Variables, Lab EF Tasks, and Academic Achievement

After the best-fitting model was established for the group-based EF assessments, we examined bivariate correlations to assess the direction and magnitude of associations among group-based EF latent variables, lab EF tasks, and academic achievement (see Table 2).

Children's performance on the three group-based EF latent variables were moderately intra-correlated ($r_s = .33 - .50$) and were slightly stronger in magnitude compared to the intra-correlations among the EF lab tasks ($r_s = .31 - .41$). Group-based EF factors were also moderately correlated with EF lab tasks ($r_s = .17 - .36$), as well as with both math and reading achievement ($r_s = .18 - .44$), which is consistent with magnitude of effects that have been reported in other studies involving young children. Further, all group-based EF factors were more strongly related to math achievement ($r_s = .21 - .44$) than to reading achievement ($r_s = .18 - .29$), with group-based working memory exhibiting the strongest relation to math achievement ($r = .44$).

Concurrent Validity of the Group-Based EF Assessments

Next, we carried out tests of concurrent validity in a structural equation model. Each lab-based EF component was regressed on all three group-based EF latent variables simultaneously to examine unique associations between group and lab-based EF components. As shown in Figure 2, this structural equation model exhibited good model fit ($\chi^2 (32) = 60.88, p = .002$; CFI = .95; TLI = .92; RMSEA = .06; SRMR = .04). Group-based inhibitory control was uniquely related to lab-based inhibitory control, whereas group-based working memory was related to both lab-based working memory and attention control. When entered in simultaneously, group-based attention control did not significantly predict any of the lab-based EF components (see Figure 2).

Predictive Validity of the Group-Based EF Assessments

Predictive validity of the group-based EF latent variables was examined in a separate structural equation model (see Figure 3). Similar to the concurrent validity SEM, both math and reading achievement were regressed on all three group-based EF factors simultaneously to

examine unique associations between group-based EF components and standardized measures of academic achievement. In this model, sex, age at group-task testing, percent of children eligible for free or reduced-price lunch, group size, and proportion of boys in each group were entered as covariates to rule out the effect of these potential confounds. As shown in Figure 3, this structural equation model exhibited acceptable model fit ($\chi^2(52) = 89.07, p = .001$; CFI = .94; TLI = .89; RMSEA = .05; SRMR = .04). Results revealed that when examined together, only the group-based working memory component significantly predicted math and reading achievement in the presence of covariates and the other two group-based components, and the prediction of group-based working memory was stronger for math than for reading achievement. Further, the prediction of group-based working memory to math achievement was robust to the inclusion of the lab-based EF tasks as additional covariates.

Discussion

The purpose of this study was to describe and validate a set of group-based EF assessments for young children. These efforts were motivated by providing researchers with a set of measures that assess EF subcomponents while also accounting for the dynamic social processes present in group settings. Although ecologically valid approaches to studying children's behavior exist using a variety of methods (e.g., naturalistic observations, teacher and parent reports, etc.); very often, it comes at the cost of experimental precision and specificity. Here, we demonstrate the feasibility of designing and administering EF tasks intended to measure behaviors related to children's EF as they manifest in a group setting. These assessments take place in schools, are relatively simple to administer, and include multiple EF indicators. The findings of this study provide preliminary evidence that a group-based paradigm is a valid approach to studying EF processes in young children. Specifically, we found that group-based EF assessments were

related to traditionally-used EF measures, and differentially predicted performance on standardized tests of math and reading achievement.

Dimensionality of the Group-Based EF Assessments

Factor analysis revealed that a 3-factor solution best fit the group-based data, which is a significant departure from the literature, as unitary EF models have consistently been found among young children up to the age of 9 (e.g., Brydges et al., 2012; Wiebe, Epsy, & Charak, 2008; Willoughby et al., 2010). The multifactorial dimensionality of the group-based tasks, however, might be due to the nature of our tasks and how they are scored. The group-based tasks are comprised of multiple sub-measures, and include multiple indicators of the same hypothesized construct (e.g., stop times across all three tasks), which can partially explain the number of recoverable dimensions observed in the group-based tasks. This is aligned with recent work reporting multi-componential EF models in young children when using multiple measures of each EF construct (e.g., Lerner and Lonigan, 2014; Miller et al., 2012; Simanowski & Krajewski, 2019). More work is needed to understand whether the differentiation hypothesis of EF development reflects underlying cognitive organization or is an artifact of the scoring procedure of commonly used EF tasks. Specifically, whether coding and extracting sub-measures within EF tasks and using multiple EF indicators could offer one way to facilitate componential differentiation in young children.

Concurrent Validity of the Group-Based EF Assessments

Tests of concurrent validity revealed significant bivariate correlations between group-based EF factors and individually-assessed EF measures. The observed associations were moderate in strength, which may be attributed to the different task demands of the group-based assessments relative to the lab tasks used in the present study. The differences in task features

across these two sets of measurements require the deployment of slightly different skills, which also contribute different sources of measurement error. For example, each one of the group-based tasks places demands on children's gross motor coordination, whereas only the lab-based inhibitory control task (i.e., HTKS) involves motor skills when inhibiting and activating behavior (Ponitz et al. 2009). This can also partially explain the pattern of unique associations observed in our structural equation models. Specifically, among all three group-based latent variables, only group-based inhibitory control uniquely predicted the HTKS measure when controlling for the other EF components.

It is important to note that while group-based attention control was significantly associated with all three direct EF assessments, it did not uniquely predict any of the standardized EF measures in our structural equation model. While this is also likely due to different task demands across measurement contexts, it could also be explained by how attention control was operationalized and measured in the group-based tasks. Among all of the EF tasks used in this study, group-based attention control was the only measure that relied on objective ratings of children's performance. Moreover, consistency in controlling and sustaining attention has been found to be low across different testing conditions and situations among young children (Barkley, 1996; Gianvecchio & French, 2002; Ruff & Rothbart, 1996), which is reflected in the moderate associations among group and lab-based attention measures used in the current study. As with many other cognitive processes, attention is a multifaceted construct that includes multiple distinct processes with varying definitions (Posner, 1982). Children's ability to selectively focus and control their attention during a visual search task (e.g., Pair Cancellation) is a more narrowly defined construct compared to our broad conceptualization of distractibility or inattentiveness in the group-based tasks.

Relatedly, it remains unclear from these analyses whether the group-based EF tasks are tapping into identical constructs measured by direct EF assessments. While the results reported in the current study provide evidence of the concurrent validity of the group-based tasks, direct EF assessments have also been shown to predict a wide range of cognitive processes and behaviors that are related to, but are distinct from, EF. As such, significant relations between the group and lab-based EF tasks can also suggest that EF simply facilitates performance on the group tasks, but are not solely capturing EF. For example, how quickly a child can stop to the music is likely driven by inhibitory control skills, but can also rely, in part, on reaction time and perceptual-motor skills. These uncertainties are not necessarily unique to the present tasks, as measurement impurity concerns have also been noted in the broader EF literature (e.g., Lerner and Lonigan, 2014; Miller et al., 2012; Miyake et al., 2000; Zelazo, Blair, & Willoughby, 2016), and are compounded by the "loose" definitions of EF components present in the current literature (e.g., Jones, Bailey, Barnes, & Partee, 2016; Morrison & Grammer, 2016).

Predictive Validity of the Group-Based EF Assessments.

Tests of predictive validity revealed significant bivariate correlations between group-based EF latent variables and performance on standardized test of math and reading achievement. Associations across group-based EF components were similar in direction and magnitude to those observed between lab EF components and math and reading achievement. These patterns of findings also mirror those reported in other studies using traditional neurocognitive EF measures – showing larger associations with math than with reading achievement (e.g., Bull and Scerif, 2001; Nguyen, & Duncan, 2019; Purpura et al., 2017). When modeled simultaneously, however, only group-based working memory uniquely predicted children's performance on standardized tests of academic skills. Together, these findings are

consistent with a growing body of literature demonstrating differential predictions to academic skills across core EF components (Ahmed et al., 2019; Nguyen, & Duncan, 2019; Waters et al., 2021; Woods et al., 2019), and further highlight the relative importance of working memory particularly for emerging math achievement (e.g., Bull and Scerif, 2001). These findings also suggest that the unique relations among core EF components and academic skills found in the extant literature are robust to different measurement types.

Limitations and Future Directions

There are limitations to the current study and its findings that are important to note. First, although having a single time-point of data provided insight into how children performed on these tasks during a key educational transition, longitudinal data would be valuable in terms of further validating these measures. Moreover, given that the group-based tasks are game-like, and have been designed for young children, understanding how they can be adapted for older children is an important future endeavor. A longitudinal design will allow us to test the stability of these measures across time points, assess longitudinal predictions to academic and other behavioral skills, and further examine componential differentiation. As the expectations of children's behavior in the classroom changes markedly across elementary school, longitudinal data would also allow to us to assess the developmental appropriateness and validity of these measures throughout this developmental period.

Secondly, although we included percentage of free or reduced school lunch at the school level as a proxy for children's socioeconomic status, child-level SES indicators, as well as other important demographic information, such as language proficiency and learning disability status are necessary to rule out potential confounds that can influence the interpretation of associations between EF and academic achievement. Relatedly, while we draw on a diverse sample of

participants, these data are not nationally representative, which limits the generalizability of our findings.

Third, more work should go into understanding whether these newly-developed group tasks converge with observational measures of classroom behavior. This would provide evidence that these tasks capture the ways in which children employ EF skills while learning in a classroom context and would lend support to the ecological sensitivity of the group-based tasks. In a similar vein, future studies would benefit from including a wider range of measures (both convergent and divergent) not included in the present study, to understand whether the group EF measures capture distinct social processes present in a group context or if they are simply an alternative set of child-friendly EF tasks. Relatedly, a promising future direction of this work would be to also administer these tasks to individual children to compare against group performance or include randomizing children into multiple groups (e.g., low- vs. high-performing groups) to evaluate the impact of different peer settings on children's EF performance.

Finally, there is evidence that the directly-assessed inhibitory control measure used in the present study (HTKS) also places demands on children's working memory, especially during the more advanced trials (Ponitz et al., 2008). The inclusion of measures that better isolate children's inhibitory control would provide stronger evidence of the criterion validity of our group-based inhibitory control tasks. Similarly, both the group tasks and individually-assessed attention control measures used in this study do not have a shifting or flexibility component. Given that the ability to shift one's attention to given aspects of a task in the presence of external, and potentially distracting stimuli is a key element to the componential EF model (Posner, &

Rothbart, 2005), an important future direction would be to develop group-based tasks that also measure cognitive flexibility.

Conclusion

Overall, this study represents a first step towards developing a set of group-based EF measures that are appropriate for use with young children. Compared to traditional, individual assessments, these group-based tasks provide researchers with a way to simultaneously collect data from a group of children, which significantly reduces testing time, and resources. Although the these tasks involve a substantial off site coding investment, the materials needed for data collection are minimal, easy to transport, and are simple to administer - making them a practical, low-cost, and potentially scalable method of data collection for school-based studies. There are also significant empirical advantages of using more ecologically sensitive measures to understand cognitive development and have implications for the ways researchers conceptualize and measure early cognitive processes. The current lack of contextually sensitive EF measures can hinder our understanding of how EF manifests in a naturalistic group setting and how it relates to specific classroom behavior and academic outcomes.

Further, given that major efforts towards understanding intervention effects on children's EF skills (e.g., Tools of the Mind; Promoting Alternative Thinking Strategies, Chicago School Readiness Project, etc.) rely on direct assessments, studying the utility of different EF measures can be of practical importance (McCoy, 2019). Specifically, understanding and measuring how children employ EF skills in typical classroom environments might be more aligned with the goals of early EF intervention programs (Jones et al., 2017). As such, future work should endeavor to understand whether context-based EF measures are more sensitive to intervention effects (McCoy, 2019), and the implications such findings might have for our basic

understanding of cognitive development. Similarly, more work should be devoted to understanding whether different types of EF assessments have any bearing on the identification of at-risk children. It is possible that certain children might struggle (or excel) with employing EF in the context of peers and competing social options, which is not captured using traditional direct EF assessments. Given that much of early childhood research is motivated to better understand how cognitive processes affect real-world outcomes, and child trajectories, it is important that measures are developed that take this ecology into consideration.

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References

- Abikoff, H., Courtney, M., Pelham, W. E., & Koplewicz, H. S. (1993). Teachers' ratings of disruptive behaviors: The influence of halo effects. *Journal of Abnormal Child Psychology*, 21(5), 519–533.
- Ahmed, S. F., Tang, S., Waters, N. E., & Davis-Kean, P. (2019). Executive function and academic achievement: Longitudinal relations from early childhood to adolescence. *Journal of Educational Psychology*. doi: 10.1037/edu0000296
- Arbuckle, J. L. (1996). Full information estimation in the presence of incomplete data. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling* (pp. 243–277). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Asparouhov, T., & Muthén, B. (2016). Structural equation models and mixture models with continuous nonnormal skewed distributions. *Structural Equation Modeling*, 23(1), 1–19. doi: 10.1080/10705511.2014.947375
- Baddeley, A. (2003). Working Memory: Looking Back and Looking Forward. *Nature Reviews Neuroscience*, 4(10), 829–839. <https://doi-org.proxy.lib.umich.edu/10.1038/nrn1201>
- Bauer, P. J., & Zelazo, P. D. (2014). The National Institutes of Health Toolbox for the Assessment of Neurological and Behavioral Function: A tool for developmental science. *Child Development Perspectives*, 8, 119–124. doi: 10.1111/cdep.12080
- Beaman, R., Wheldall, K., & Kemp, C. (2006). Differential teacher attention to boys and girls in the classroom. *Educational review*, 58(3), 339–366. doi:10.1080/00131910600748406
- Berhenke, A. L. (2013). *Motivation, Self-Regulation, and Learning in Preschool* (Doctoral dissertation).

- Best, J. R., Miller, P. H., & Naglieri, J. A. (2011). Relations between executive function and academic achievement from ages 5 to 17 in a large, representative national sample. *Learning and Individual Differences, 21*(4), 327–336. doi: 10.1016/j.lindif.2011.01.007
- Blair, C. (2002). School readiness: Integrating cognition and emotion in a neurobiological conceptualization of children's functioning at school entry. *American Psychologist, 57*, 111–127. doi: 10.1037/0003-066X.57.2.111
- Blair, C., & Diamond, A. (2008). Biological processes in prevention and intervention: The promotion of self-regulation as a means of preventing school failure. *Development and Psychopathology, 20*(3), 899–911. doi: 10.1017/S0954579408000436
- Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. *Sage focus editions, 154*, 136-136.
- Bull, R., & Scerif, G. (2001). Executive functioning as a predictor of children's mathematics ability: Inhibition, switching, and working memory. *Developmental neuropsychology, 19*(3), 273-293. https://doi-org.proxy.lib.umich.edu/10.1207/S15326942DN1903_3
- Brydges, C. R., Reid, C. L., Fox, A. M., & Anderson, M. (2012). A unitary executive function predicts intelligence in children. *Intelligence, 40*(5), 458-469. doi:10.1016/j.intell.2012.05.006
- Carlson, S. M., Zelazo, P. D., & Faja, S. (2013). The Oxford handbook of developmental psychology: Vol. 1. Body and mind.

- Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural equation modeling*, 9(2), 233-255.
doi:10.1207/S15328007SEM0902_5
- Clark, C. A., Pritchard, V. E., & Woodward, L. J. (2010). Preschool executive functioning abilities predict early mathematics achievement. *Developmental psychology*, 46(5), 1176.
<https://doi-org.proxy.lib.umich.edu/10.1037/a0019672>
- Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and psychological measurement*, 20(1), 37-46. <https://doi-org.proxy.lib.umich.edu/10.1177/001316446002000104>
- Diamond, A. (2013). Executive functions. *Annual review of psychology*, 64, 135-168.
- Duckworth, A. L., & Yeager, D. S. (2015). Measurement matters: Assessing personal qualities other than cognitive ability for educational purposes. *Educational Researcher*, 44(4), 237–251.
- Enders, C. K. (2001). A primer on maximum likelihood algorithms available for use with missing data. *Structural Equation Modeling*, 8(1), 128-141.
- Finch, J. E., Garcia, E. B., Sulik, M. J., & Obradović, J. (2019). Peers Matter: Links Between Classmates' and Individual Students' Executive Functions in Elementary School. *AERA Open*, 5(1), 2332858419829438.
- Garcia, E. B., Sulik, M. J., & Obradović, J. (2019). Teachers' perceptions of students' executive functions: Disparities by gender, ethnicity, and ELL status. *Journal of Educational Psychology*, 111(5), 918–931. doi: 10.1037/edu0000308

- Gershon, R. C., Cella, D., Fox, N. A., Havlik, R. J., Hendrie, H. C., & Wagster, M. V. (2010). Assessment of neurological and behavioural function: The NIH toolbox. *The Lancet Neurology*, 9(2), 138-139. doi:10.1016/S1474-4422(09)70335-7
- Gianvecchio, L., & French, L. (2002). Sustained attention, inattention, receptive language, and story interruptions in preschool Head Start story time. *Journal of Applied Developmental Psychology*, 23(4), 393–407. doi: 10.1016/S0193-3973(02)00125-9
- Hallgren, K. A. (2012). Computing inter-rater reliability for observational data: an overview and tutorial. *Tutorials in quantitative methods for psychology*, 8(1), 23.
- Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, 6(1), 1-55. doi:10.1080/10705519909540118
- IBM Corp. Released 2016. IBM SPSS Statistics for Macintosh, Version 24.0. Armonk, NY: IBM Corp.
- Jones, S. M., Bailey, R., Barnes, S. P., & Partee, A. (2016). Executive Function Mapping Project: Untangling the Terms and Skills Related to Executive Function and Self-Regulation in Early Childhood. OPRE Report # 2016-88, Washington, DC: Office of Planning, Research and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services.
- Jones, S. M., Barnes, S. P., Bailey, R., & Doolittle, E. J. (2017). Promoting social and emotional competencies in elementary school. *The Future of Children*, 27, 49–72.
- Lan, X. (2009). Bridging naturalistic and laboratory measures of self-regulation: The development and validation of challenge tasks. Unpublished doctoral dissertation, The University of Michigan.

- Lerner, M. D., & Lonigan, C. J. (2014). Executive function among preschool children: Unitary versus distinct abilities. *Journal of psychopathology and behavioral assessment*, 36(4), 626-639. doi:10.1007/s10862-014-9424-3
- Lipsey, M. W., Nesbitt, K. T., Farran, D. C., Dong, N., Fuhs, M. W., & Wilson, S. J. (2017). Learning-related cognitive self-regulation measures for prekindergarten children: A comparative evaluation of the educational relevance of selected measures. *Journal of Educational Psychology*, 109(8), 1084. doi: 10.1037/edu0000203
- Little, R. J. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American statistical Association*, 83(404), 1198-1202.
- McAuley, T., Chen, S., Goos, L., Schachar, R., & Crosbie, J. (2010). Is the behavior rating inventory of executive function more strongly associated with measures of impairment or executive function? *Journal of the International Neuropsychological Society*, 16(3), 495-505. doi: 10.1017/S1355617710000093
- McCabe, L. A., & Brooks-Gunn, J. (2007). With a little help from my friends? Self-regulation in groups of young children. *Infant Mental Health Journal*, 28, 584–605. doi.org/10.1002/imhj.20155
- McCoy, D. C. (2019). Measuring Young Children's Executive Function and Self-Regulation in Classrooms and Other Real-World Settings. *Clinical child and family psychology review*, 22(1), 63-74. <https://doi-org.proxy.lib.umich.edu/10.1007/s10567-019-00285-1>
- Miller, M. R., Giesbrecht, G. F., Müller, U., McInerney, R. J., & Kerns, K. A. (2012). A latent variable approach to determining the structure of executive function in preschool children. *Journal of Cognition and Development*, 13(3), 395–423. doi: 10.1080/15248372.2011.585478

- Moffett, L., & Morrison, F. J. (2019). Off-task behavior in kindergarten: Relations to executive function and academic achievement. *Journal of Educational Psychology*. doi: 10.1037/edu0000397
- Monsell, S. (1996). Control of mental processes. In V. Bruce (Ed.), *Unsolved mysteries of the mind: Tutorial essays in cognition*. (pp. 93–148). Erlbaum (Uk) Taylor & Francis, Publ.
- Montroy, J. J., Bowles, R. P., & Skibbe, L. E. (2016). The effect of peers' self-regulation on preschooler's self-regulation and literacy growth. *Journal of Applied Developmental Psychology*, 46, 73–83. doi: 10.1016/j.appdev.2016.09.001
- Morrison, F. J., & Grammer, J. K. (2016). Conceptual clutter and measurement mayhem: Proposals for cross disciplinary integration in conceptualizing and measuring executive function. *Executive Function in Preschool*.
- Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., & Howerter, A. (2000). The unity and diversity of executive functions and their contributions to complex frontal lobe tasks: A latent variable analysis. *Cognitive Psychology*, 41(1), 49–100.
doi:10.1006/cogp.1999.0734
- Muthén, L. K., & Muthén, B. O. (2005). *Mplus: Statistical analysis with latent variables: User's guide* (pp. 1998-2012). Los Angeles: Muthén & Muthén.
- Muthén, L. K. (2010, April 25). Convergence [Msg. 21]. Message posted to <http://www.statmodel.com/discussion/messages/12/17.html?1438886834>
- Nguyen, T., & Duncan, G. J. (2018). Kindergarten components of executive function and third grade achievement: A national study. *Early Childhood Research Quarterly*.
doi:10.1016/j.ecresq.2018.05.006

- Neidlinger, N. M., (2015). Do Friends Help or Hinder? Examining Co-regulation in Kindergarteners. Unpublished doctoral dissertation, The University of Michigan.
- Obradović, J., Sulik, M. J., Finch, J. E., & Tirado-Strayer, N. (2018). Assessing students' executive functions in the classroom: Validating a scalable group-based procedure. *Journal of Applied Developmental Psychology*, 55, 4-13.
doi.org/10.1016/j.appdev.2017.03.003
- Pianta, R. C., & Rimm-Kaufman, S. (2006). The social ecology of the transition to school: Classrooms, families, and children. In K. McCartney & D. Phillips (Eds.), *Blackwell handbook of early childhood development*. (pp. 490–507). Malden, MA: Blackwell.
- Ponitz, C. C., McClelland, M. M., Jewkes, A. M., Connor, C. M., Farris, C. L., & Morrison, F. J. (2008). Touch your toes! Developing a direct measure of behavioral regulation in early childhood. *Early Childhood Research Quarterly*, 23(2), 141–158.
doi:10.1016/j.ecresq.2007.01.004
- Posner, M. I. (1982). Cumulative development of attentional theory. *American Psychologist*, 37(2), 168–179. doi: 10.1037/0003-066X.37.2.168
- Posner, M. I., & DiGirolamo, G. J. (1998). Executive attention: Conflict, target detection, and cognitive control. In R. Parasuraman (Ed.), *The attentive brain*. (pp. 401–423). The MIT Press.
- Posner, M. I., & Rothbart, M. K. (2003). Developing mechanisms of self-regulation. In M. E. Hertzig & E. A. Farber (Eds.), *Annual progress in child psychiatry and child development: 2000–2001*. (pp. 21–42). Brunner-Routledge.

- Purpura, D. J., Schmitt, S. A., Ganley, C. M. (2017). Foundations of mathematics and literacy: The role of executive functioning components. *Journal of Experimental Child Psychology, 153*, 15-34. doi:10.1016/j.jecp.2016.08.010
- Rimm-Kaufman, S. E., Curby, T. W., Grimm, K. J., Nathanson, L., & Brock, L. L. (2009). The contribution of children's self-regulation and classroom quality to children's adaptive behaviors in the kindergarten classroom. *Developmental psychology, 45*(4), 958. doi: 10.1037/a0015861
- Rothbart, M. K., Posner, M. I., & Kieras, J. (2006). Temperament, Attention, and the Development of Self-Regulation. In K. McCartney & D. Phillips (Eds.), *Blackwell handbook of early childhood development*. (pp. 338–357). Blackwell Publishing. doi: 10.1002/9780470757703.ch17
- Ruff, H. A., & Rothbart, M. K. (1996). *Attention in early development: Themes and variations*. Oxford University Press.
- Satorra, A., & Bentler, P. M. (2001). A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika, 66*, 507–514.
- Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods, 7*, 147–177. doi: 10.1037/1082-989X.7.2.147
- Sherman, E. M., & Brooks, B. L. (2010). Behavior rating inventory of executive function—preschool version (BRIEF-P): Test review and clinical guidelines for use. *Child Neuropsychology, 16*(5), 503–519.
- Shing, Y. L., Lindenberger, U., Diamond, A., Li, S.-C., & Davidson, M. C. (2010). Memory maintenance and inhibitory control differentiate from early childhood to

- adolescence. *Developmental Neuropsychology*, 35(6), 679–697. doi: 10.1080/87565641.2010.508546
- Silver, C. H. (2014). Sources of data about children's executive functioning: review and commentary. *Child Neuropsychology*, 20:1–13. doi: 10.1080/09297049.2012.727793.
- Simanowski, S., & Krajewski, K. (2019). Specific preschool executive functions predict unique aspects of mathematics development: A 3-year longitudinal study. *Child Development*, 90(2), 544–561. doi: 10.1111/cdev.12909
- Stevens, J.P., (1992) Applied multivariate statistics for the social sciences (2nd edition). Hillsdale, NJ: Erlbaum.
- Sullivan, J. R., & Riccio, C. A. (2007). Diagnostic group differences in parent and teacher ratings on the BRIEF and Conners' scales. *Journal of Attention Disorders*, 11(3), 398–406. doi: 10.1177/1087054707299399
- Toplak, M. E., West, R. F., & Stanovich, K. E. (2013). Do performance-based measures and ratings of executive function assess the same construct? *Journal of Child Psychology and Psychiatry*, 54(2), 131–143. <https://doi-org.proxy.lib.umich.edu/10.1111/jcpp.12001>
- Waters, N. E., Ahmed, S. F., Tang, S., Morrison, F. J., & Davis-Kean, P. E. (2020). Pathways from socioeconomic status to early academic achievement: The role of specific executive functions. *Early Childhood Research Quarterly*, 54, 321-331.
- Wechsler, D. (1991). Manual for the Wechsler intelligence scale for children-(WISC-III). San Antonio, TX: Psychological Corporation.
- Weiland, C., Ulvestad, K., Sachs, J., & Yoshikawa, H. (2013). Associations between classroom quality and children's vocabulary and executive function skills in an urban public

- prekindergarten program. *Early Childhood Research Quarterly*, 28(2), 199–209. doi: 10.1016/j.ecresq.2012.12.002
- Weintraub, S., Bauer, P. J., Zelazo, P. D., Wallner-Allen, K., Dikmen, S. S., Heaton, R. K., . . . Gershon, R. C. (2013). I. NIH Toolbox Cognition Battery (CB): Introduction and pediatric data. *Monographs of the Society for Research in Child Development*, 78, 1–15. <http://dx.doi.org/10.1111/mono.12031>
- Wiebe, S. A., Epsy, K. A., & Charak, D. (2008). Using Confirmatory Factor Analysis to Understand Executive Control in Preschool Children: I. Latent Structure. *Developmental Psychology*, 44(2): 575
- Wiebe, S. A., Sheffield, T. D., & Epsy, K. A. (2012). Separating the fish from the sharks: A longitudinal study of preschool response inhibition. *Child Development*, 83(4), 1245–1261. doi: 10.1111/j.1467-8624.2012.01765.x
- Willoughby, M. T., Blair, C. B., Wirth, R. J., & Greenberg, M. (2010). The measurement of executive function at age 3 years: psychometric properties and criterion validity of a new battery of tasks. *Psychological assessment*, 22(2), 306. doi:10.1037/a0018708
- Willoughby, M. T., Wirth, R. J., & Blair, C. B. (2012). Executive function in early childhood: Longitudinal measurement invariance and developmental change. *Psychological Assessment*, 24(2), 418–431. doi: 10.1037/a0025779
- Woodcock, R. W., McGrew, K. S., & Mather, N. (2001). Examiner's manual. *Woodcock-Johnson III Tests of Achievement*.
- Woods, A. D., Ahmed, S. F., Katz, B. D., & Morrison, F. J. (2019). How Stable is Early Academic Performance? Using Cluster Analysis to Classify Low Achievement and EF. *Journal of Learning Disabilities*, 0022219419881632.

- Yuan, K. H., & Bentler, P. M. (2000). 5. Three likelihood-based methods for mean and covariance structure analysis with nonnormal missing data. *Sociological methodology*, 30(1), 165-200.
- Zelazo, P. D. (2015). Executive function: Reflection, iterative reprocessing, complexity, and the developing brain. *Developmental Review*, 38, 55–68. doi: 10.1016/j.dr.2015.07.001
- Zelazo, P. D., Anderson, J. E., Richler, J., Wallner-Allen, K., Beaumont, J. L., Conway, K. P., ... & Weintraub, S. (2014). NIH Toolbox Cognition Battery (CB): Validation of executive function measures in adults. *Journal of the International Neuropsychological Society*, 20(6), 620-629. doi: 10.1017/S1355617714000472
- Zelazo, P. D., Blair, C. B., & Willoughby, M. T. (2016). *Executive function: Implications for education (NCER 2017–2000)*. Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Research.

Table 1.
Descriptive Statistics for all Study Variables

Variable	N	M	SD	Min	Max	Skewness	Kurtosis
Freeze Task							
Stop Time	252	4374.3	1741.2	1625	13539	1.5	3.7
Distractibility	251	13.2	2.6	5	15	-1.5	1.4
Jumping Task							
Stop Time	252	2130.6	1060.9	234	11092	3.4	22.9
Distractibility	252	7.3	2.0	3	9	-.92	-.40
Action Recall	252	14.8	4.7	0	24	-.20	-.11
Action Performance	252	4.8	5.5	0	44	3.7	18.9
Marching Task							
Stop Time	251	5919.9	2132.5	1962	16394	1.0	2.5
Distractibility	251	16.0	4.6	7	21	-.50	-1.1
March Recall	251	2.8	1.9	0	7	.38	-.82
March Performance	251	7.8	4.1	0	14	-.28	-.85
Laboratory EF Tasks							
HTKS	277	30.8	16.9	0	58	-.52	-.81
Backward Digit Span	276	2.1	1.6	0	8	.28	-.38
Pair Cancellation	274	18.4	9.6	0	43	-.07	-.57
Academic Achievement							
Mathematics	278	17.8	4.3	1	30	-.91	1.7
Reading	281	18.8	8.2	2	53	1.3	2.7
Covariates							
Male	283	.47	.50	0	1	1.1	-2.0
Percent FRPL	282	45.3	28.7	2	71.9	-.70	-1.3
Age at Group Testing	250	5.8	.38	4.99	6.98	.11	-.37
Group Size	252	4.8	.81	3	7	.41	.13
Proportion Boys	252	.54	.17	0	1	-.26	.86

Note: Unstandardized raw scores for all model indicators. All group-based indicators summed across trials (i.e., Freeze task = 5 trials, Jumping task = 3 trials, Marching task = 7 trials). Stop Times measured in milliseconds, Distractibility = 4-point Likert scale, Action Recall = 5-point Likert scale, Action Performance = 5-point Likert scale, Action Recall scored as a continuous, March Performance = 3-point Likert scale, March Recall dichotomous (0 = cued; 1 = not cued). HTKS = Head-Toes-Knees-Shoulders-Task (Ponitz et al., 2008). Male = dummy coded sex variable: 0 = male, 1 = female. Percent FRPL = Percent of Children Eligible for Free or Reduced-Price Lunch. Proportion Boys = Proportion of Boys Present in Each Group. Backward Digit Span = Wechsler intelligence scale for children (Wechsler, 1991). Math, Reading, and Pair Cancellation = Woodcock-Johnson III (Woodcock & Mather, 2000).

Table 2.
Correlations for Main Model Indicators

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1. FT Stop-Time	-														
2. FT Distractibility	.36	-													
3. JT Stop-Time	.43	.26	-												
4. JT Distractibility	.19	.54	.31	-											
5. JT Action Recall	.32	.16	.32	.22	-										
6. JT Action Performance	.26	.24	.17	.20	.61	-									
7. MT Stop-Time	.41	.23	.65	.27	.18	.10	-								
8. MT Distractibility	.23	.49	.28	.59	.14	-.18	.33	-							
9. MT March Recall	.14	-.01	.05	-.01	.26	-.11	-.06	.01	-						
10. MT March Performance	.11	-.04	.06	.05	.11	-.03	-.09	.13	.11	-					
11. HTKS	.25	.20	.21	.19	.18	.15	.24	.26	.11	.03	-				
12. Backward Digit Span	.25	.18	.19	.16	.31	.25	.21	.16	.12	.13	.41	-			
13. Pair Cancellation	.16	.10	.12	.16	.30	.16	.10	.19	.24	.09	.31	.34	-		
14. Math	.35	.13	.21	.14	.40	.29	.19	.18	.16	.19	.48	.54	.36	-	
15. Reading	.18	.10	.19	.13	.28	.18	.13	.16	.18	.18	.22	.43	.34	.57	-

Note: FT = Freeze Task; JT = Jumping Task; MT = Marching Task; HTKS = Head-Toes-Knees-Shoulders. Significant two-tailed correlations are in boldface. Correlations between .13 and .17 are significant at the $p < .05$ level; correlations between .18 and .21 are significant at the $p < .01$ level, and correlations .22 and above are significant at the $p < .001$ level. Stop-Time Indicators reverse-coded; JG Action Performance reverse-coded.

Figure 1: *Confirmatory Factor Analysis of Group-Based EF Tasks (N = 252)*

Model fit Statistics: $\chi^2(17) = 43.2, p < .001$; CFI = .93; TLI = .89; RMSEA = .08; SRMR = .05
 * $p < .05$, ** $p < .01$, *** $p < .001$.

Note: FT = Freeze Task; JT = Jumping Task; MT = Marching Task. Stop-Times converted from millisecond to seconds and reverse-coded, JT Perform reverse-coded. Standard errors adjusted to account for clustering around groups. MLR estimator - maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic that are robust to non-normality.

Table 3.

Correlations among Group-Based EF Latent Variables, Lab EF Tasks, and Academic Achievement

	1.	2.	3.	4.	5.	6.	7.	8.
1. Group IC	-							
2. Group WM	.36***	-						
3. Group AC	.50***	.33***	-					
4. HTKS	.30***	.21**	.30***	-				
5. Backward Digit Span	.28***	.36***	.23***	.41***	-			
6. Pair Cancellation	.17*	.28**	.21*	.31***	.34***	-		
7. Math	.30***	.44***	.21**	.48***	.54***	.37***	-	
8. Reading	.22***	.29***	.18**	.22***	.43***	.35***	.58***	-

Note: * $p < .05$, ** $p < .01$, *** $p < .001$.

Group IC = Group-Based Inhibitory Control Latent Variable; Group WM = Group-Based Working Memory Latent Variable; Group AC = Group-Based Attention Control Latent Variable, HTKS = Head-Toes-Knees-Shoulders.

Figure 2: Concurrent Validity Structural Equation Model ($N = 252$)

Model fit Statistics: $\chi^2(32) = 60.88, p = .002$; CFI = .95; TLI = .92; RMSEA = .06; SRMR = .04
 * $p < .05$, ** $p < .01$, *** $p < .001$.

Note: FT = Freeze Task; JT = Jumping Task; MT = Marching Task. Standard errors adjusted to account for clustering around groups. MLR estimator - maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic that are robust to non-normality.

Figure 3: *Predictive Validity Structural Equation Model (N = 252)*

Model fit statistics: $\chi^2(52) = 89.07, p = .001$; CFI = .94; TLI = .89; RMSEA = .05; SRMR = .04
 * $p < .05$, ** $p < .01$, *** $p < .001$.

Note: FT = Freeze Task; JT = Jumping Task; MT = Marching Task. Standard errors adjusted to account for clustering around groups. MLR estimator - maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic that are robust to non-normality.

Table 4.

Standardized Coefficients Reported in the Predictive Validity Structural Equation Model

	Math Achievement	Reading Achievement
Group Inhibitory Control	0.07(.13)	0.04(.08)
Group Working Memory	0.35(0.08)***	0.20(0.09)*
Group Attention Control	0.04(0.09)	0.10(0.08)
Male	0.07(0.05)	0.00(0.06)
Age at Testing	0.18(0.07)**	0.18(0.07)**
% FRPL	-0.28(0.06)***	-0.17(0.08)*
Group Size	0.02(0.06)	0.07(0.06)
% Male	0.07(0.05)	0.09(0.05)

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Male = dummy coded sex variable: 0 = male, 1 = female

% FRPL = percentage of children eligible for free or reduced-price lunch

% Male = percentage of boys in each experimental group

Appendix A: Group-Based Executive Function Assessments Coding Scheme

Freeze Task

Stop Time

- Stop time is calculated **in milliseconds** from when the song begins playing to when the child stops and freezes

Distractibility

- 3** –Full Attention, No Interference (body and face are directed at the experimenter, attentive expression, no disruptive actions or verbalizations)
- 2** –Distracted by peer (Partial Attention, Some Instances of Interference (some time with full attention, some occurrences of distraction or disruptive actions or verbalizations)
- 1** –Distracted by self (Partial Attention, Some Instances of Interference (some time with full attention, some occurrences of distraction or disruptive actions or verbalizations)
- 0** –No Attention, Multiple Instances of Interference

Instances of distractions or interference include unusual arm or head movements (swinging arms or head bobbing to music) dancing or skipping instead of marching, body or face not directed at the experimenter, inattentive expression, looking at the ceiling or door, failure to march in a circle, talking, singing, excessive laughter, pointing, shouting.

Jumping Task

Stop Time

- Stop time is calculated **in milliseconds** from when the song stops playing to when the child freezes prior to completing actions

Distractibility

- 3** –Full Attention, No Interference (body and face are directed at the experimenter, attentive expression, no disruptive actions or verbalizations)
- 2** –Distracted by peer (Partial Attention, Some Instances of Interference (some time with full attention, some occurrences of distraction or disruptive actions or verbalizations)
- 1** –Distracted by self (Partial Attention, Some Instances of Interference (some time with full attention, some occurrences of distraction or disruptive actions or verbalizations)
- 0** –No Attention, Multiple Instances of Interference

Instances of distractions or interference include unusual arm or head movements (swinging arms or head bobbing to music) dancing or skipping to the music instead of marching, body or face not directed at the experimenter, inattentive expression, looking at the ceiling or door, failure to march in a circle, talking, singing, excessive laughter, pointing, shouting.

Action Recall Performance will be calculated for **each** action during each trial (e.g., Trial 1: 1 action, Trial 2: 2 actions, Trial 3: 3 actions)

- 4** –Perfect Recall (given to a child who performs the actions correctly without learning the actions from a peer)
- 3** –Cued Perfect (given to a child who performs the actions correctly after learning (visually, verbally) from a peer; there will be a delay in performing the actions)
- 2** –Incorrect (given to a child who performs the actions incorrectly without being cued by a peer)
- 1** –Cued Incorrect (given to a child who performs the actions incorrectly after learning (visually, verbally) from a peer; there will be a delay in performing the actions)
- 0** –No Response (given to a child who does not respond or produces an irrelevant or completely incorrect response)

Action Performance: *Performance will be calculated for **each** action during each trial (e.g., Trial 1: 1 action, Trial 2: 2 actions, etc.)*

The accuracy with which children carry out the one-through-three step instructions. Each time a child performs fewer actions than instructed (e.g., jumps twice when instructed to jump three times), performs more actions than instructed (e.g., jumps twice when instructed to jump once), or performs different actions than instructed (e.g., claps when instructed to jump) they are assigned a score of 1 (for each deviation from the given instructions). This is repeated across each trial and across all step instructions. A zero therefore indicates perfect performance, and the higher the score, the less accurate the performance. Scores are tallied across all trials and summed to indicate accuracy of performance.

- 0** – Perfect performance (given to a child who performs the action the correct amount of times; e.g., jumps three times, claps twice and crouches down)

Deviation Below– given to a child who performs the action(s) fewer times than were instructed (e.g., instructed to jump three times; jumps twice—given score of -1; jumps once—given score of -2, etc.)

Deviation Above– given to a child who performs the action(s) more times than were instructed (e.g., instructed to jump three times; jumps four times—given score of 1; instructed to clap twice; claps four times—given score of 2, etc.

Marching Task

Marching Direction Time

- Marching Direction time is calculated **in milliseconds** from when the song begins playing to when the child begins marching

Stop Time

- Stop time is calculated **in milliseconds** from when the song stops playing to when the child freezes (this will be followed by “reset” motion)

Distractibility

- 3** –Full Attention, No Interference (body and face are directed at the experimenter, attentive expression, no disruptive actions or verbalizations)
- 2** –Distracted by peer (Partial Attention, Some Instances of Interference (some time with full attention, some occurrences of distraction or disruptive actions or verbalizations)

- 1** –Distracted by self (Partial Attention, Some Instances of Interference (some time with full attention, some occurrences of distraction or disruptive actions or verbalizations)
- 0** –No Attention, Multiple Instances of Interference

Instances of distractions or interference include unusual arm or head movements (swinging arms or head bobbing to music) dancing or skipping to the music instead of marching, body or face not directed at the experimenter, inattentive expression, looking at the ceiling or door, failure to march in a circle, talking, singing, excessive laughter, pointing, shouting.

Performance (Marching Direction)

- 2** –Correct (given to a child who marches in the correct direction)
- 1** – Self- Correct (given to a child who corrects to the appropriate direction)
- 0** –Incorrect (given to a child who marches in the incorrect direction)

Recall (Marching Direction)

- 1** –Not Cued (given to a child who performs the action without learning the actions from a peer)
- 0** –Cued (given to a child who performs the action after learning (visually, verbally) from a peer; there will be a delay in performing the actions)

Appendix B: Group-Based Inhibitory Control Administration Protocol

Supplies

- Speakers
- Music CD/MP3 Player
- Protocol sheet
- Labels for children
- Class list for matching children and numbers

Freeze Task:

During the Freeze Task, researchers instruct children to march in a circle without music. When the music starts, children must freeze into a certain pose. Children can only unfreeze themselves when the researcher says “unfreeze” or when the music stops again. A separate researcher controls the marching music and starts it at random intervals of less than 15 seconds. The task is repeated for three trials and is videotaped.

Researcher directions:

1. Get the children in a circle.
2. Say, “We are going to play a game called **Freeze**. In this game, you are going to walk in a circle (model by walking around the outside of the circle clockwise) when the music is **not** playing. When the music **starts playing**, freeze like a statue. Then when the music **stops** again, you can unfreeze and start walking around in a circle again.”
3. Conduct one practice trial. If most of students understand instructions, proceed with game. If not, reiterate the rules on the game **only once**, and then proceed to game.

Researcher directions:

1. Make sure both cameras are still recording.
2. Control the music, letting children march for 7-15 seconds at a time and then starting the music.

Jumping Task:

During the Jumping Task, children also march in a circle to music, but prior to marching, researcher instruct students to “jump three times” (one-step instruction) when they hear the music stop. So, as children march, they have to monitor the music and remember the instructions. After the one-step instruction trial, the researcher gives the two-step instruction (“jump three times and clap twice”) and three-step instruction (“jump three times, clap twice, and crouch down”) respectively.

Researcher directions:

4. Get the children in a circle again.
5. Say, “Show me what it means to clap three times” and model it correctly.
6. Say, “Show me what it means to jump once” and model it correctly.
7. Say, “We are going to play another game. You are going to walk in a circle when the music is playing. When the music stops, **jump three times** and then stop.”

8. After the children do that, say, “Good job! Now let’s try it another way. This time, when the music stops, **jump three times and clap your hands twice**, then stop.”
9. After the children do that, say, “Great! Now let’s try one more thing. This time, when the music stops, **jump three times, clap your hands twice, and crouch down**, then stop.”

Note: try to make sure that the one-, two-, or three-step instructions are the last thing the children hear before the music starts.

Researcher directions:

3. Make sure both cameras are still recording.

Marching Task:

During the Marching Task, children stand in a circle facing the middle. They are instructed to march on one direction if one song begins playing (left for Song #1), and the opposite direction if another song begins to play (right for Song #2). After a few seconds, the song will stop and children will be directed to turn back and face the center before starting the next trial.

Researcher directions:

10. Get the children in a circle again and have researcher stand in center of circle.
11. Say, “Face toward me” and wait for students to face researcher.
12. Say, “We are going to play another game. You are going to hear one of two songs. When you hear this song (**Song #1**), you will turn **left**, or this way (model by turning in circle), and start marching. When the music stops, stop marching and face me.”
13. Say, “If you hear this song (**Song #2**), you will turn **right**, or this way (model by turning in circle), and start marching. Remember, when the music stops, you stop marching and face me.”
14. Say, “Okay, let’s try!” (Practice)
15. Play **Song #1**, and correct as needed. “Remember, when the music stops, stop marching and face me.”
16. Play **Song #2**, and correct as needed. Remember, when the music stops, stop marching and face me.”

Researcher directions:

4. Make sure both cameras are still recording.
5. Control the music, letting it play for 7-15 seconds at a time.