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Attentional Fluctuations in Preschoolers: Direct and Indirect Relations with Task Accuracy, Academic Readiness, and School Performance

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Abstract

Attentional control fluctuates in the presence of internal and external distractors, wandering on and off a given task. The present study investigated individual differences in attentional fluctuations in 250 preschoolers. Attentional fluctuations were assessed via intra-individual variability in response time in a Go/No-Go task. Greater fluctuations in attentional control were linked to lower task accuracy. In addition, greater attentional fluctuations predicted lower performance in a task of cognitive flexibility, the Dimensional Card Sort Task. Attentional fluctuations were also associated with laboratory measures of academic readiness at preschool as assessed by the Applied Problems and Letter-Word Identification subscales of Woodcock-Johnson III Test of Achievement, which in turn predicted teacher reports of academic performance in first grade. Attentional fluctuations also had indirect associations with emergent math skills at preschool, via cognitive flexibility, as well as indirect associations with first-grade teacher reports of academic performance, via the relations between cognitive flexibility and emergent math skills in preschool. These results suggest that consistency is an important aspect of attentional control in early childhood.

Keywords

attentional fluctuations; intra-individual variability; response time variability; academic readiness and performance

Introduction

Attentional control is the ability to sustain attention on a task in the presence of internal and external distractors (Engle & Kane, 2004). In children, attentional control is associated with foundational cognitive assets, such as language, memory, and intelligence (Astheimer & Sanders, 2012; Astle, Nobre, & Scerif, 2010; Rueda, Rothbart, McCandliss, Saccomanno, & Posner, 2005). Further, it is a strong predictor of school readiness and success (Allhusen et

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al., 2003; Blair & Diamond, 2008; Rueda, Checa, & Rothbart, 2010). Given the notable connections between attentional control and other critical cognitive functions and academic skills, it is important to advance our understanding of this fundamental ability in early childhood. To date, a rich body of research informs us about various aspects of attentional control in young children (for reviews, see Posner, Rothbart, Sheese, & Voelker, 2014; Stevens & Bavelier, 2012). However, we still know very little about how a characteristic feature of attentional control, its susceptibility to fluctuations, manifests in early childhood.

Attention wanders on and off a given task, fluctuating even in the absence of salient external distractors (Esterman, Noonan, Rosenberg, & Degutis, 2013). Previous work with adults has demonstrated that greater fluctuations in attention predicted impairments in task performance (Bellgrove, Hester, & Garavan, 2004; Haynes, Bauermeister, & Bunce, 2016; Unsworth & McMillan, 2014). Importantly, individuals who were more susceptible to attentional fluctuations showed poorer performance not only during the task in which fluctuations were measured, but also in other fundamental cognitive functions including working memory, prospective memory, and fluid intelligence (Ihle, Ghisletta, & Kliegel, 2016; Kane et al., 2016; Larson & Saccuzzo, 1989; Unsworth, 2015). Further, fluctuations of attentional control are heightened in a wide spectrum of clinical populations, such as in individuals with Alzheimer's, schizophrenia, depression, and borderline personality disorder (Duchek et al., 2009; Kaiser et al., 2008). These findings suggest that heightened attentional fluctuations in adults are associated with impairments in broader cognitive performance. Such findings underscore the importance of characterizing attentional fluctuations in early childhood, as this line of inquiry lays the groundwork for understanding pathways to consistent control of attention throughout development. Further, such investigations can inform interventions meant to promote attentional control in childhood and beyond. The goal of the present study is to examine how individual differences in attentional fluctuations manifest in the preschool period, a pivotal time of rapid development in attentional skills (Posner et al., 2014).

In adults, the frequency of lapses in attentional control during a task can be approximated via thought-probe measures that ask participants to report whether they are on or off task or to rate their attentional engagement at any given moment (Kam, Dao, Stanciulescu, Tildesley, & Handy, 2013; Unsworth & McMillan, 2014). Although such measures give a reasonable proxy for lapses in attentional control in adults, they are inevitably limited by subjective experiences of lapses, and may not capture attentional fluctuations that occur outside of awareness yet still have behavioral consequences (Kane et al., 2016). Further, such measures cannot be used with young children whose metacognitive abilities are still developing (Flavell, Green, & Flavell, 2000). Therefore, a simple and age-appropriate measure that does not rely on subjective experience is needed to index fluctuations in attentional control in young children. Previous work has shown that attentional fluctuations during a task can be measured via intra-individual variability in response time (Esterman et al., 2013; Fortenbaugh et al., 2015; Unsworth, 2015). Attentional fluctuations can contribute to response time variability through at least two mechanisms. First, lapses in attentional control can lead to goal neglect (Unsworth, Redick, Lakey, & Young, 2010). When a child is "in-the-zone," task-relevant goals are maintained consistently. However, when lapses in attentional control happen, in other words when the child is "out-of-the-zone," the goal of the task is not maintained efficiently and goal neglect occurs. In the presence of goal neglect, habitual responses can dominate the behavior. Thus, prepotent tendencies to respond take over, and responses much faster than the average are observed. Second, lapses in attentional control can slow down cognitive processes. When a child is "out-of-the-zone" due to lapses in attentional control, attention needs to be re-directed to get back "in-the-zone." This re-direction of attention for task-relevant behavior takes time. In such cases, responses can occur much slower than the average. As such, fluctuations in attentional control, at least partially, account for much faster and slower responses. Such fluctuations may not be observable through mean response time values, but rather through *intra-individual variability* in response time. Importantly, measures of response time variability taken from a variety of attentional control tasks all load onto a common factor, and this factor is considered to tap into the consistency of attentional control (Unsworth, 2015).

An individual's response time variability is thought to be a marker of how susceptible that individual is to frequently disengaging attention from task-relevant goals. As such, it is considered an index of executive attention abilities (Kane et al., 2016). Research with adults has demonstrated that greater response time variability predicts poorer cognitive performance in nonclinical populations (Haynes et al., 2016; Larson & Saccuzzo, 1989; Unsworth, 2015), and is a common characteristic across various adult clinical populations (Duchek et al., 2009; Kaiser et al., 2008). Such findings highlight the utility of using response time variability as an index of attentional fluctuations in typical and atypical populations alike. However, with children, response time variability has been primarily utilized in the context of developmental disorders centered (e.g. Adamo et al., 2012; Kofler et al., 2013; Nigg, 2013). This line of research has particularly on children and adolescents with attention deficit and hyperactivity disorder (ADHD), and converging findings demonstrate greater response time variability in ADHD populations compared to controls (e.g. Borella, de Ribaupierre, Cornoldi, & Chicherio, 2013; Drechsler, Brandeis, Földényi, Imhof, & Steinhausen, 2005; Epstein et al., 2011). Indeed, response time variability has been proposed as an endophenotype of ADHD (Castellanos et al., 2005) and has been observed as a common neuropsychological marker, even across distinct subgroups of the disorder (Fair, Bathula, Nikolas, & Nigg, 2012; Kofler et al., 2013). Further, greater response time variability has been documented in other clinical or at-risk developmental populations, such as children with autism spectrum disorder, and children with or at risk for bipolar disorder (Geurts et al., 2008; Pagliaccio et al., 2016). Considering response time variability as an index of attentional fluctuations, these findings imply that vulnerability to attentional fluctuations is common across populations of atypically developing children, or children who are at risk for atypical development. Yet, beyond the studies of children with or at risk for disorders, we know very little about how attentional fluctuations manifest in children. Several life-span studies that employed response time variability have demonstrated decreases in attentional fluctuations across childhood and adolescence and into young adulthood (Conners, Epstein, Angold, & Klaric, 2003; Fortenbaugh et al., 2015; Williams, Hultsch, Strauss, Hunter, & Tannock, 2005). However, there is a paucity of information about individual differences in attentional fluctuations during the early years of childhood, and how such individual differences relate to cognitive performance and emergent academic skills. The present study contributes to closing this gap in our knowledge by using response time variability as a measure of attentional fluctuations in a demographically diverse population of young children.

Our work builds on the executive/supervisory control of attention framework (Engle & Kane, 2004; Norman & Shallice, 1986; Unsworth & Robison, 2017). Within this framework, attentional control is defined as the ability to focus on task goals in the presence of internal and external distractors. This definition encompasses both the ability to sustain attention on a given task and the ability to select stimuli and responses that are relevant for that task. Executive control of attention is especially consequential during cognitive tasks that require the regulation of competing brain activity and the control of resulting behavior (Posner & Rothbart, 2009; Posner et al., 2014). Attentional control can switch between a stable state of being “in the zone” (on-task) and an erratic state of being “out of the zone” (Esterman et al., 2013). In other words, attentional control fluctuates. As Unsworth (2015) proposes, such fluctuations index whether attentional control is deployed in a consistent manner or not. Specifically, although attentional control is generally discussed in terms of how attention is deployed *on average* in a given task, the consistency aspect of attentional control concerns *intra-individual variability* during a task (Unsworth, 2015; Unsworth & Robison, 2017).

Here we assessed intra-individual variability in attentional control by measuring response time variability in a sustained attention to response task (Go/No-Go), which is commonly used to measure response time variability in older children and adolescents (e.g. Fair et al., 2012; Simmonds et al., 2007; Sjowall, Roth, Lindqvist, & Thorell, 2013). Using this measure, we investigated individual differences in attentional fluctuations in early childhood. First, we examined the link between attentional fluctuations and task performance. Greater fluctuations in attentional control have been associated with poorer task performance in adults (Bellgrove et al., 2004; Haynes et al., 2016; Unsworth, 2015), suggesting the importance of consistency of attentional control for cognitive functioning in adulthood. We hypothesized that if consistency were an important aspect of attention in early childhood, then it would also strongly relate to task performance in young children as well. Accordingly, greater fluctuations in attentional control, as indexed by increased response time variability, would predict poorer overall task performance.

Second, we assessed how attentional fluctuations measured by response time variability in one task related to performance in another cognitive task. We reasoned that attentional fluctuations measured in a cognitive task would be a proxy for a child’s general susceptibility to attentional fluctuations, and therefore would be associated with performance in another cognitive task. This would imply that attentional fluctuations mark an underlying cognitive trait observable across tasks. Work with adults has found that response time variability measured in one task is linked to performance in other tasks that rely on attentional control, such as tests of working memory, long-term memory, and intelligence (Larson & Saccuzzo, 1989; Li et al., 2004; Unsworth, 2015; Walhovd & Fjell, 2007). Here we focused on the association between attentional fluctuations measured in one task and performance on a separate task of cognitive flexibility, with the latter argued to be an ability relying on aspects of attentional control in children, such as selective attention and attention shifting (Benitez, Vales, Hanania, & Smith, 2017; Kirkham, Cruess, & Diamond, 2003). We expected children with increased attentional fluctuations, as observed in the

Go/No-Go task, to show poorer performance in cognitive flexibility, as measured by a Dimensional Card Sort Task (Espinet, Anderson, & Zelazo, 2012).

Third, we investigated how attentional fluctuations assessed in the preschool years would relate to academic readiness prior to school entry, as well as to later academic performance. Attentional fluctuations index inconsistency of attentional control. Since consistency is considered an important aspect of attentional control (Unsworth, 2015) and attentional control is a strong predictor of academic readiness and achievement (Duncan et al., 2007; Posner & Rothbart, 2014; Rueda et al., 2010), we inferred that the consistency of attentional control would relate to emergent academic abilities, as well as early academic performance. Specifically, we predicted that preschoolers with greater attentional fluctuations would show poorer academic readiness, as measured by standardized tests of emergent literacy and numeracy skills at preschool, and poorer academic performance, as measured by teacher reports of school performance in first grade. Another plausible hypothesis concerns the indirect associations between attentional fluctuations and first-grade academic performance via early academic readiness. Frequent fluctuations in attention may lead to children missing information in their environment relevant to the acquisition of early math and reading skills. In turn, given that emergent math and reading skills in preschool constitute the building blocks of later academic performance, such setbacks in the acquisition of these skills in preschool may predict lower performance in elementary school (Aunola, Leskinen, Lerkkanen, & Nurmi, 2004; Duncan et al., 2007; Guo, Sun, Breit-Smith, Morrison, & Connor, 2015). Thus, we also assessed indirect pathways whereby attentional fluctuations would relate to math and reading readiness prior to school entry, which in turn would directly influence academic performance in first grade.

An additional goal of the present study was to assess the indirect associations between attentional fluctuations and academic outcomes via cognitive flexibility. It has been proposed that one mechanism through which attentional control contributes to academic outcomes is via other cognitive control processes commonly referred to as executive functions (Amso & Scerif, 2015; Garon, Bryson, & Smith, 2008). Cognitive flexibility (also known as shifting) is considered an integral component of executive functions (Miyake & Friedman, 2012; Miyake et al., 2000) and has been linked to performance in tasks of math and reading (Purpura, Schmitt, & Ganley, 2017; Yeniad, Malda, Mesman, van Ijzendoorn, & Pieper, 2013). Therefore, we reasoned that, in addition to the hypothesized direct associations, fluctuations in attentional control would relate to school readiness and first-grade academic performance also through its contributions to cognitive flexibility.

Method

Participants

Participants were recruited as a part of a longitudinal study on trajectories of early academic success. The initial sample consisted of 278 children, between the ages of 45 and 70 months (Mean = 56, *SD = 5)*, from the Southeastern United States. None of the children had started kindergarten at the time of recruitment or at the preschool data collection time point. Children were excluded from the current study if their parents reported atypical neuropsychological development either in the preschool or first-grade parent questionnaires (microcephaly: *n* = 1; absence seizures: *n* = 2). As greater response time variability is commonly observed in children with ADHD (Fair et al., 2012; Kofler et al., 2013), to ensure our results were not driven by children with ADHD and to test the utility of assessing attentional fluctuations beyond clinical populations, we excluded children for whom their parents reported diagnosis for ADHD and related medication treatment (*n* = 12). An additional 12 children did not participate in the Go/No-Go task. Data from one child was missing due to equipment error. The final preschool sample consisted of 250 children (137 female; Mean age = 56 months, *SD* = 5 months). Parent reports of race indicated that 61% of the children were White, 28% Black, 2% Asian, 9% multi-racial. Of the children included in the preschool sample of the present study, 231 children returned for the first-grade assessment (Mean age = 84 months, *SD* = 4). The first-grade sample was limited to the children for whom both the preschool response time data and first-grade teacher reports were available (*n* = 188). These children did not differ from children who were included in the preschool sample, but not in the first-grade sample in terms of age, gender, minority status, or income-to-needs ratio.

Procedure

Preschool-aged children were recruited from daycare centers, local community establishments (e.g. libraries, parks) and via participant referral. The preschool laboratory visit lasted approximately 2 hours and consisted of a battery of tasks assessing cognitive development and academic readiness, as well as tasks of social-cognitive and emotional development that are not reported here. Informed consent was obtained from parents or legal guardians at the beginning of the visit. The first-grade data collection took place approximately two years after the preschool laboratory visit. During the first-grade data collection, parents were also asked permission to contact children’s first-grade teacher. Teachers were contacted via email and asked to complete a series of questionnaires via Qualtrics in the spring semester of the first-grade year. Children received a toy, and parents and teachers received monetary compensation, for their participation.

Measures

Demographics—Primary caregivers provided information about their children’s age, gender, ethnicity, and their monthly family income via a questionnaire. Child ethnicity was recoded for analysis purposes to denote minority status (Non-Hispanic White = 0, Minority = 1). Preschool income-to-needs ratio was used as a proxy for socioeconomic status in early childhood. Family monthly income was reported on an item that consisted of 15 ranges from which to choose (e.g. $1000–1499). The midpoint of each range was used as the measurement of monthly income, and was multiplied by 12 to compute annual income. The appropriate poverty threshold was based on the U.S. Census Reports for the year in which annual income was earned, and assessed by the total number of members in the household, and the number of full-time children living in the home. We derived the income-to-needs ratio by diving the annual family income by the poverty threshold.

Attentional fluctuations—Response time variability was used to measure fluctuations in attentional control. To capture response time variability, we used a computerized Go/No-Go task (Lahat, Todd, Mahy, Lau, & Zelazo, 2010). The task was presented via E-Prime Version

2.0 (PST, Pittsburgh, PA). Task stimuli consisted of animal drawings (cow, horse, bear, pig, or dog). At the beginning of each trial, a fixation point, accompanied by a “ding” sound, appeared in the middle of the screen, and stayed for 1500 ms. This was followed by an animal stimulus that stayed on the screen for 1500 ms, or until a response was registered. Children were instructed to respond via button-press as soon as they saw an animal, except for when they saw a dog. A yellow smiley face followed each correct answer. A red frowning face followed each incorrect response, or responses that occurred after the 1500 ms stimulus window. Children completed 10 practice trials, consisting of 6 Go and 4 No-Go trials. The practice block was repeated until children responded to 9 out of 10 trials correctly. All children included in the final sample passed the practice. The task consisted of 144 trials (75% Go, 25% No-Go), divided into four blocks. In a Go/No-Go paradigm, response time can be measured for correct Go and incorrect No-Go trials, as no responses exist for incorrect Go trials when required responses were missed, and correct No-Go trials when responses were successfully inhibited. Consistent with studies that used Go/No-Go paradigms (Fuentes-Claramonte et al., 2016; Kane et al., 2016), the index of attentional fluctuations was response time variability derived from only the correct Go trials. Response time variability was assessed via Coefficient of Variation (CoV), which has been a common measure of intra-individual variability, used across a wide range of age groups (e.g. Borella et al., 2013; Fortenbaugh et al., 2015; Pagliaccio et al., 2016). CoV was computed by dividing the standard deviation of response time by the mean response time (Mean RT) for each child. This measure allowed us to account for each child’s average response time when assessing variability. Greater scores on this measure corresponded to greater fluctuations in attentional control (i.e. poorer attentional control).

A preliminary analysis revealed that greater response time variability in the Go/No-Go task was related to greater omission errors (missing responses for Go trials, $r = -.54$, $p < .001$), as well as greater commission errors (failing to inhibit responses in No-Go trials, $r = -.74$, $p < .001$). Therefore, for parsimony, an overall task accuracy score (% correct) was computed as the average of Go % correct and No-Go % correct.

Cognitive flexibility—A computerized version of the Dimensional Card Sort Task (Espinet et al., 2012) was used to measure cognitive flexibility. On each trial, children were presented with a test stimulus, a blue rabbit or a red boat, at a central location above two target stimuli: a blue boat on the left and a red rabbit on the right. In the pre-switch block, which consisted of 15 trials, children were instructed to sort stimuli according to one dimension (i.e., shape). In the post-switch block, which consisted of 30 trials, children were instructed to sort stimuli based on the other dimension (i.e., color). The experimenter explained the instructions to the child before the post-switch block began, and repeated them every 5th trial. Children responded via pressing one of the two buttons on a response pad. Each button had a laminated replica of one of the target stimuli (left button: blue boat; right button: red rabbit). Test stimuli remained on the screen until children responded. The experimenter initiated new trials after a minimum of 1000 ms. Cognitive flexibility was measured as the percentage of correct responses in the post-switch block. Children who performed at or below chance (less than 8 correct trials out of 15) in the pre-switch block were considered to fail the pre-switch step (n = 4) and did not receive any points for the post-switch block, regardless of their actual performance.

Emergent academic skills—To assess emergent mathematical and reading skills, we used two subscales from the Woodcock Johnson III Tests of Achievement: Applied Problems and Letter-Word Identification (Woodcock, McGrew, & Mather, 2001). In the Applied Problems subtest, children were shown pictorial mathematical problems and instructed to point to or say the answer. The Letter-Word Identification subtest included items that involved symbolic learning, matching pictographic representations of words with the actual pictures of objects, and reading identification skills in identifying isolated letters and words. For both Woodcock Johnson subtests, raw scores were used in the analyses.

Teacher reports of academic performance—At first grade, teacher reports of children's academic performance were assessed with the Mock Report Card (Pierce, Hamm, & Vandell, 1999). Out of the 19-item questionnaire, 6 items were selected to assess how children perform in major academic content, including reading, oral language, written language, math, social studies, and science. Academic grades reported on these items have demonstrated good construct validity via their positive associations with standardized achievement test scores (Pierce, Bolt, & Vandell, 2010). Teachers rated children's academic performance on a 5-point scale, ranging from 1 (below/child is performing below grade level) to 5 (excellent/child is performing beyond grade level). Items were highly correlated with each other at this grade level (rs > .74). Therefore, we created a composite School Performance score by averaging across these items (α = .95).

Results

Preliminary analyses were conducted to examine outliers and normality of distributions. Outliers above or below 3.29 SD were replaced with the next highest or lowest value (Castellanos et al., 2005). Such replacements were made for 4 children for the WJ Letter-Word Identification task, 1 child for the WJ Applied Problems task, and 3 children for attention fluctuation values (i.e., CoV values). Descriptive statistics for all measures are reported in Table 1.

Zero order correlations are shown in Table 2 for the preschool and the first-grade variables. These correlations showed the expected relationships between attention fluctuations and the outcome measures, with greater fluctuations (higher CoV values) relating to poorer performance across the tasks.

First, we conducted a regression analysis to assess the extent to which fluctuations in attentional control were associated with task performance. This analysis was conducted in SPSS and missing data (income-to-needs ratio: n = 7; cognitive flexibility: n = 1) were handled via expectation maximization. Age at which the outcome measures were collected (preschool or first grade), gender (0 = male, 1 = female), ethnicity (0 = not minority, 1 = minority), and income-to-needs ratio were entered in step 1 as control variables; the index of attentional fluctuations, CoV, was entered in step 2 as the predictor. The covariates together explained a significant portion of variance in overall task accuracy in the Go/No-Go task, R^2

= .19, $F(4, 245) = 14.76$, $p < .001$. The addition of attentional fluctuations significantly contributed to the model, $\Delta R^2 = .43$, $\Delta F(1, 244) = 284.19$, $p < .001$. Greater attentional fluctuations were associated with lower overall accuracy in the task. See Table 3 for a summary of this regression analysis.

Then, we conducted path analyses to evaluate the hypothesized direct and indirect associations between attentional fluctuations, cognitive flexibility and school readiness assessed at preschool, and academic performance assessed at first grade. Analyses were conducted with Mplus version 8 (Muthén & Muthén, 1998–2017). Missing data (income-to-needs ratio: $n = 7$; cognitive flexibility: $n = 1$; age at first grade: $n = 5$) were handled via full information maximum likelihood.

In the path model (see Figure 1), the index of attentional fluctuations, i.e. coefficient of variation, was specified as an exogenous variable that predicted cognitive flexibility, as well as emergent math and reading skills at preschool, and academic performance in first grade. Cognitive flexibility was also specified as predicting emergent math and reading skills at preschool, and academic performance in first grade. Finally, emergent math and reading skills at preschool were specified as predicting academic performance in first grade.

Initially, the model controlled for age at testing, income-to-needs ratio, and minority status at preschool and first grade. As shown in Table 2, gender did not correlate with any of the outcome measures and was not included in this path model. This model had good fit, ($\chi^2(4, N = 250) = 10.19$, $p = .037$, comparative fit index (CFI) = .98, root-mean-square error of approximation (RMSEA) = .08, confidence interval (CI) = [.02, .14], standardized root mean square residual (SRMR) = .03). In this model, the following covariate paths did not have statistically significant coefficients: a) minority status predicting cognitive flexibility, reading readiness, and first grade school performance; b) age and income-to-needs ratio predicting first grade school performance. For parsimony, we adopted a model trimming approach for respecification (Kline, 2016) and removed these paths from the model. Removing these paths did not significantly change the model fit, $\chi^2(4, N = 250) = 5.31$, $p = .256$. Therefore, these covariate paths were excluded from the model.

Figure 1 shows this model with the standardized coefficients. The unstandardized coefficients and confidence intervals are presented in Table 4. This model fit well ($\chi^2(8, N = 250) = 15.50$, $p = .050$, CFI = .98, RMSEA = .06, CI = [.00, .11], SRMR = .04). Independent of covariates, attentional fluctuations were associated with cognitive flexibility, emergent math skills, and emergent reading skills at preschool such that the children who had greater fluctuations (i.e. less consistency) in attentional control had poorer cognitive flexibility, as well as school readiness. However, contrary to prediction, attentional fluctuations at preschool were not directly associated with first grade school performance. Similarly, cognitive flexibility was positively associated with emergent math and reading skills at preschool, but was not associated with first grade school performance.

Indirect associations were assessed using a bias-corrected bootstrapping approach (MacKinnon, Lockwood, & Williams, 2004) with 10,000 draws (see Table 4 for statistics). First, we evaluated the indirect effects of attentional fluctuations on emergent math and reading skills via cognitive flexibility. The indirect effect of attentional fluctuations on emergent math skills via cognitive flexibility was significant. The remaining direct effect of attentional fluctuations on emergent math skills was also significant, suggesting that consistency of attentional control was linked to math readiness both directly and through its association with cognitive flexibility. The indirect effect of attentional fluctuations on emergent reading skills via cognitive flexibility was not significant.

Second, we evaluated the indirect effects of attentional fluctuations on academic performance in first grade, testing various possible paths. The indirect effect of attentional fluctuation on school performance via cognitive flexibility was not significant. However, attentional fluctuations had an indirect effect on first-grade academic performance via preschool math readiness and also via preschool reading readiness. The remaining direct effect of attentional fluctuations on first grade academic performance was not significant. Thus, consistency of attentional control was linked to math and reading readiness during preschool years, which in turn predicted first grade academic performance.

Cognitive flexibility had an indirect effect on first grade academic performance via math readiness but not via reading readiness. The remaining direct effect of cognitive flexibility on first-grade academic performance was not significant. We also found that attentional fluctuations had an indirect effect on first grade academic performance via its associations with cognitive flexibility, which in turn was linked to emergent math skills at preschool. However, we did not find a significant indirect effect of attentional fluctuations on first grade academic performance via the path of cognitive flexibility to emergent reading skills.

Discussion

The present study examined fluctuations in attentional control in preschoolers. We assessed the extent to which fluctuations in attentional control relate to a) performance on the task in which the fluctuations were observed, b) performance on a separate, but related, task of cognitive performance; and c) emergent academic abilities. First, we found a strong relationship between fluctuations in attentional control and task performance. Greater fluctuations in attentional control during the task, as indexed by higher response time variability, were linked to more omission errors, i.e. missing required responses. Similarly, greater fluctuations in attentional control were linked to more commission errors, i.e. failing to withhold a prepotent response. These results are consistent with findings from a previous study linking response time variability to both omission and commission errors in a similar task in a study of ADHD (Simmonds et al., 2007). Our finding that attentional fluctuations were related to both types of errors in the task suggests that fluctuations in attentional control are associated with overall task performance in preschoolers. Previous studies with adults and older children reported similar associations between fluctuations in attentional control and task performance across a variety of tasks (Bellgrove et al., 2004; Epstein et al., 2011; Kane et al., 2016). Our results indicate that the strong relations between attentional fluctuations and task performance in adults and older children are already present in early childhood.

Second, we found that children who showed greater attentional fluctuations in the Go/No-Go task demonstrated poorer performance in the cognitive flexibility task. This finding suggests that attentional fluctuations measured in one cognitive task could be a proxy for fluctuations in another cognitive task. Such a finding implies that the consistency aspect of attentional control may be a cognitive trait, relating to performance across tasks. Several studies with adults demonstrated that individuals with greater attentional fluctuations showed poorer performance in various aspects of cognition, such as working memory, prospective memory, and intelligence (Ihle et al., 2016; Kane et al., 2016; Unsworth, 2015). Here we demonstrated a similar link between individual differences in attentional fluctuations and cognitive flexibility in early childhood. In previous studies with children, features of attentional control, such as attention shifting and selective attention, were associated with cognitive flexibility (Benitez et al., 2017; Hanania & Smith, 2010; Kirkham et al., 2003). Our results extend such findings to the consistency aspect of attentional control. These findings support the idea that consistency is an important aspect of attentional control in early childhood.

Third, we investigated the associations between fluctuations in attentional control and academic readiness and performance. We found that children with greater fluctuations in attentional control performed worse in tests of math and reading readiness at preschool, which in turn predicted lower teacher ratings of academic performance in first grade. These findings suggest that consistency of attentional control has concurrent associations with emergent math and reading skills during preschool years, which sets the stage for later academic outcomes. Several aspects of attentional control have been linked to academic readiness (Duncan et al., 2007; Posner & Rothbart, 2014; Stevens & Bavelier, 2012). Our results link the consistency aspect of attentional control to emergent academic abilities. One reason for this may be that attentional fluctuations impair learning processes. Children who are more susceptible to frequent lapses in attentional control may often miss important information in the environment necessary to acquire academic skills. Further, frequent lapses in attentional control can impede performance in academic tasks by leading to periods of goal neglect, as well as recurrent failures in selecting stimuli and responses relevant for the task goals. As such, attentional fluctuations may impair both the acquisition and execution of early academic skills. Although the design of the present study precludes any claims of directionality, our findings lay the foundation for further investigation of the relations between attentional fluctuations and academic readiness and achievement.

Another goal of the current study was to test the indirect relations between attentional fluctuations and academic performance via cognitive flexibility. Based on the premise that consistency is an important aspect of attentional control (Unsworth, 2015; Unsworth & Robison, 2017), which is foundational for executive functions such as cognitive flexibility (Amso & Scerif, 2015; Garon et al., 2008), and given the associations between cognitive flexibility and academic outcomes (e.g. Purpura et al., 2017; Yeniad et al., 2013), we reasoned that fluctuations in attentional control can relate to performance in academic tasks not only directly but also through cognitive flexibility. Therefore, we hypothesized indirect pathways whereby attentional fluctuations would predict lower performance in cognitive flexibility, which in turn would be associated with poorer math and reading readiness at preschool, and lower academic performance in the first grade. As hypothesized, we found that attentional fluctuations predicted cognitive flexibility, which in turn was associated with emergent math skills at preschool. Similarly, there was an indirect relation between attentional fluctuations and teacher reports of first grade academic performance via the association between cognitive flexibility and preschool math readiness. These results are consistent with the argument that attentional control can contribute to academic outcomes not only directly but also via executive functions, such as cognitive flexibility (Amso & Scerif, 2015; Garon et al., 2008) and suggest that consistency aspect of attentional control play a role in these associations. However, contrary to prediction, we did not find indirect associations between attentional fluctuations and reading readiness via cognitive flexibility. Likewise, we did not find indirect associations between attentional fluctuations and first grade academic performance via the association between cognitive flexibility and reading readiness. Cognitive flexibility also had an indirect association with academic performance at first grade via preschool math readiness, but not via preschool reading readiness. These results may suggest that the cognitive flexibility component of executive functions is particularly important for early math abilities as children learn to shift flexibly between rules and concepts (Blair, Ursache, Greenberg, & Vernon-Feagans, 2015; Purpura et al., 2017). However, it has also been argued that although laboratory assessments of emerging math abilities may capture the processes that recruit cognitive flexibility, assessments of early reading skills may rely more on knowledge-based skills instead of comprehension, and thus may not recruit flexible use of rules as much (Blair et al., 2015). Therefore, future studies with different reading readiness assessments may reveal pathways we could not detect in this study. Further, future research should consider assessing a more comprehensive assay of cognitive mechanisms through which attentional fluctuations may relate to academic outcomes.

In this study, building on the executive attention framework (Engle & Kane, 2004; Unsworth, 2015), which posits attentional control as the ability to focus on task goals in the presence of external and internal distractors, we demonstrated direct and indirect relations between the consistency aspect of attentional control, accuracy in cognitive tasks, academic readiness and early school performance. Instead of how attentional control is deployed on average in a given task, consistency concerns *intra-individual variability* in attentional control (Unsworth, 2015; Unsworth & Robison, 2017). When attention is tightly focused on a task, an individual engages in goal-directed behavior consistently. However, when goal-directed attention is not tightly focused, lapses of attention can manifest either in the form of very fast responses that are guided by prepotent tendencies to respond regardless of the task demands, or by frequently occurring slow responses due to the re-direction of attention to task-relevant stimuli and behaviors (Esterman et al., 2013; Unsworth, 2015; Unsworth, Schrock, & Engle, 2004). Therefore, intra-individual variability in response time, driven by responses both much faster and slower than average, is considered an index of fluctuations in attentional control during the task (Esterman et al., 2013; Fortenbaugh et al., 2015; Unsworth, 2015). The current study demonstrated the utility of using response time variability as a marker of attentional fluctuations in young children. Although young children cannot be expected to report on their ongoing attentional engagement like adults can, response time variability provides an age-appropriate, unbiased alternative to measure attentional fluctuations in early childhood. Importantly, in our study average response time was not related to any of our outcome measures, after taking the control variables into account. Intra-individual variability in response time, however, predicted performance in cognitive tasks in preschool and had direct and indirect associations with academic readiness in preschool and performance in first grade. Such findings emphasize the importance of taking intra-individual variability into account in studies of individual differences in cognitive development in early childhood.

Here we discussed response time variability as an index of attentional fluctuations and demonstrated how increased response time variability relates to poorer outcomes in cognitive measures and academic skills. However, it is important to note that whether response time variability marks a deficit in cognitive processes depends on the task in question. In tasks where success depends on the stability in goal maintenance and exploitation of known rules and strategies, response time variability indexes whether attentional control is consistently deployed. The task we used to measure response time variability in this study (Go/No-Go) fits this category. However, many tasks, such as visual search, also involve trade-offs between exploiting known opportunities and exploring for better opportunities elsewhere, known as the exploration versus exploitation trade-off (Hills et al., 2015). In these circumstances, response time swings may mark exploratory strategies to gather information about the environment (Frank, Doll, Oas-Terpstra, & Moreno, 2009; Hills et al., 2015). Therefore, it is important to underscore that response time variability is to be considered an index of attentional fluctuations in tasks that require consistent control of attention, stability of goal maintenance, and using known rules and strategies.

A limitation of the present study is that we used only one task during which response time variability could be measured accurately. Although this is a common approach in developmental studies that measure response time variability (e.g. Fair et al., 2012; Sjowall et al., 2013), it prevents us from assessing how task characteristics, such as task difficulty and response demands, may play a role in the extent to which attentional control fluctuates in young children. Work with adults demonstrated that response time variability measured across executive control tasks emerges as a single construct of attentional control (Kane et al., 2016; Unsworth, 2015). A similar unitary construct may emerge in early development as well. Future studies in which response time variability is measured across tasks in young children could elucidate the effects of task characteristics on attentional fluctuations in young children, if any. Moreover, such study designs would be important for teasing apart the effects of specific task demands (e.g. response inhibition) from influences of attentional fluctuations.

Another important future direction is the investigation of underlying neurobiological mechanisms of attentional fluctuations in young children. Such investigations can help us better understand what aspects of brain development interact with contextual factors to contribute to consistency of attentional control in early childhood. One of the proposed neurobiological mechanisms of consistency of attentional control centers on the functioning within the dorsal frontoparietal attentional network (DAN), which is generally involved in goal-directed top-down attention processes (Petersen & Posner, 2012), and the default mode network (DMN), which is considered an integrative network that adjusts its activity according to the functioning of other networks (Mittner, Hawkins, Boekel, & Forstmann, 2016), and how these two dynamic attentional systems work in tandem (Esterman et al., 2013; Esterman, Rosenberg, & Noonan, 2014; Kucyi, Hove, Esterman, Hutchison, & Valera, 2016). A second proposal focuses on the contributions of neurotransmitter systems to intra-individual variability in performance, including neurotransmitters such as dopamine and norepinephrine (MacDonald, Nyberg, & Bäckman, 2006; Mittner et al., 2016; Unsworth & Robison, 2017). It remains to be investigated what aspects of these brain networks and neurotransmitter systems may contribute to individual differences in susceptibility to attentional fluctuations in children.

Future studies in this line of research can also inform education and intervention efforts that aim to promote school readiness and early academic performance. To date, several training programs yielded promising results in improving cognitive abilities in preschoolers with diverse neurocognitive profiles, including children who are at-risk for school failure or with developmental disorders, such as ADHD (e.g. Capodieci, Gola, Cornoldi, & Re, 2017; Neville et al., 2013; Raver et al., 2011). It is plausible that such programs already include components that reduce attentional fluctuations. However, it is also possible that additional components of training may be needed to reduce attentional fluctuations, especially in children who are most susceptible to frequent lapses in attentional control. Further, incorporating measures of attentional fluctuations to assessment batteries can be useful in determining which children may benefit from certain trainings more and which children may need supplementary programs. Given the direct and indirect associations we reported between attentional fluctuations and performance in tasks of cognition and academic skills, consistency of attentional control may be an important target for training programs that aim to improve cognitive development and academic achievement during childhood and beyond.

In conclusion, in the present study we demonstrated that greater attentional fluctuations strongly predicted lower task accuracy. In addition, we found that attentional fluctuations measured in one cognitive task could be used as a proxy for attentional fluctuations in another cognitive task. Further, we identified direct and indirect associations between attentional fluctuations and academic outcomes. Such findings highlight that consistency is an important aspect of attentional control in early childhood. Our study lays the groundwork for future research on how this important aspect of attentional control may relate to fundamental cognitive abilities and emergent academic skills throughout childhood. Our findings also highlight the need to understand the biological, psychological, and contextual mechanisms that account for individual differences in susceptibility to attentional fluctuations in children. Given the strong links between attentional control and performance in cognitive tasks as well as academic readiness and achievement (Duncan et al., 2007; Posner & Rothbart, 2014), this line of research carries the potential to have broader implications for cognitive development and academic performance.

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Research Highlights

- We investigated individual differences in attentional fluctuations in preschoolers.
- Attentional fluctuations were assessed via intra-individual variability in response time.
- Greater attentional fluctuations were related to lower accuracy across tasks.
- Attentional fluctuations had direct and indirect relations to academic outcomes.
- These findings suggest consistency is an important aspect of attentional control.

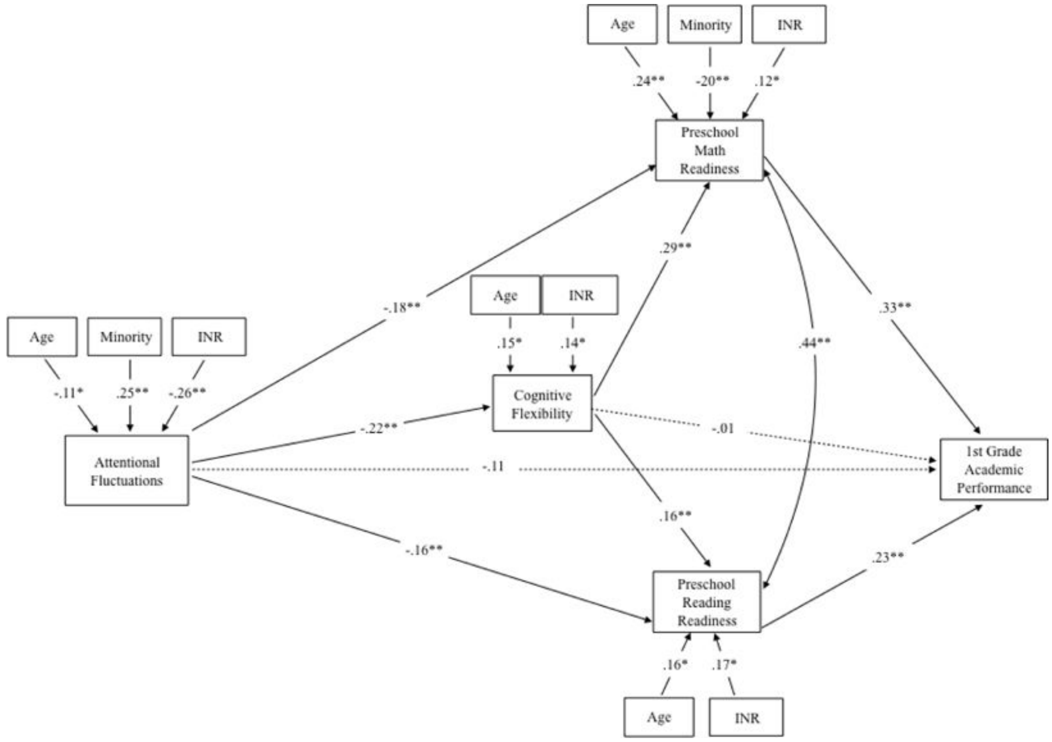

Figure 1.

The path model predicting math and reading readiness at preschool and teacher reports of academic performance in first grade. Values are standardized coefficients. Statistically significant paths are straight lines. INR = income-to-needs ratio.

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

Table 1

Descriptive Statistics

Variables	***n***	**Min**	**Max**	***M***	***SD***
Preschool age (months)	250	45.00	70.00	56.43	4.70
1st grade age (months)	183	75.70	96.23	83.57	4.27
Income-to-needs ratio	243	.10	6.40	2.17	1.43
Mean RT	250	471.45	1052.25	802.41	100.92
Attentional fluctuations (CoV)	250	.18	.71	.33	.10
Task accuracy (%)	250	48.77	100.00	83.12	10.95
Cognitive flexibility (%)	249	.00	100.00	68.61	33.04
Math Readiness	250	2.00	27.00	14.77	4.16
Reading readiness	250	1.00	28.00	11.06	5.09
1st grade academic performance	188	1.00	5.00	3.60	.91

Table 2

Correlations Among Preschool Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1. Age (preschool)	–											
2. Age (1st grade)	.81***	–										
3. Gender	−.10	−.08	–									
4. Minority Status	−.06	−.06	.04	–								
5. Income-to-Needs Ratio	.09	.09	.09	−.28***	–							
6. Mean Response Time	−.06	.06	.04	−.18**	.16*	–						
7. Attentional Fluctuations	−.15*	−.17*	−.12	.33***	−.33***	−.52***	–					
8. Task accuracy	.25***	.20**	.20**	−.26***	.24***	.18*	−.77**	–				
9. Cognitive Flexibility	.20**	.13	.07	−.19**	.22**	.02	−.29**	.33***	–			
10. Math Readiness	.35***	.29***	.03	−.32***	.31***	.03	−.40**	.48***	.45***	–		
11. Reading Readiness	.24***	.14*	.10	−.05	.28***	.03	−.29**	.37***	.28***	.55***	–	
12. 1st Grade Academic Performance	−.01	−.04	.09	−.18*	.19*	.07	−.28**	.26***	.21**	.49***	.43***	–

Note. Gender: 1 = female; Minority: 1 = minority. For attentional fluctuations, higher scores indicate greater fluctuations in attentional control.

* $p < .05$,

** $p < .01$,

*** $p < .001$

Table 3

Summary of The Regression Analysis Predicting Task Performance (Go/No-Go Accuracy) From Control Variables and Attentional Fluctuations

	Model 1				Model 2			
Variable	***B***	***SE B***	***β***	***P***	***B***	***SE B***	***β***	***p***
Age	.56	.14	.24	< .001	.35	.09	.15	< .001
Gender	4.78	1.28	.22	< .001	2.90	.88	.13	.001
Minority	−4.58	1.32	−.21	.001	−.44	.93	−.02	.634
INR	1.15	.47	.15	.014	−.27	.33	−.04	.414
Coefficient of Variation					−79.83	4.74	−.74	< .001
ΔR^2		.18		< .001		.43		< .001

Note: INR = Income-to-needs ratio; Gender: 1 = female; Minority: 1 = Minority; higher values in coefficient-of-variation indicate greater attentional fluctuations.

Table 4

Direct and indirect associations from the path model

			Confidence Interval		
Path	**Est.**	***SE***	**Lower**	**Upper**	***p***
CoV → Flexibility	−70.554	19.713	−109.192	−31.915	< .001
CoV → Math readiness	−7.212	2.531	−12.713	−2.251	.004
CoV → Reading readiness	−8.218	3.115	−14.323	−2.113	.008
CoV → 1st G. academic	−.963	.654	−2.244	.318	.140
Flexibility → Math readiness	.036	.007	.023	.050	< .001
Flexibility → Reading readiness	.025	.010	.006	.044	.010
Flexibility → 1st G. academic	.000	.002	−.004	.004	.918
Math readiness → 1st G. academic	.073	.017	.039	.107	< .001
Reading readiness → 1st G. academic	.042	.014	.014	.070	.004
Age → CoV	−.002	.001	−.005	.000	.045
Age → Flexibility	1.072	.417	.255	1.889	.010
Age → Math readiness	.211	.048	.118	.305	< .001
Age → Reading readiness	.177	.066	.048	.305	.007
INR → CoV	−.018	.004	−.026	−.010	< .001
INR → Flexibility	3.122	1.425	.329	5.915	.028
INR → Math readiness	.339	.172	.002	.677	.049
INR → Reading readiness	.606	.222	.171	1.041	.006
Minority status→ CoV	.051	.012	.028	.074	< .001
Minority status → Math readiness	−1.614	.420	−2.437	−.792	< .001
Indirect associations					
CoV → Flexibility → Math readiness	−2.575	.854	−4.249	−.901	.003
CoV → Flexibility → Reading readiness	−1.750	.924	−3.562	.062	.058
CoV → Flexibility → 1st G. academic	.014	.145	−.270	.298	.922
CoV → Math readiness → 1st G. academic	−.526	.229	−.974	−.078	.021
CoV → Reading readiness → 1st G. academic	−.342	.173	−.681	−.003	.048
Flexibility → Math readiness → 1st G. academic	.003	.001	.001	.004	.002
Flexibility → Reading readiness → 1st G. academic	.001	.001	.000	.002	.086

Path	Est.	*SE*	Confidence Interval		*p*
			Lower	Upper	
CoV → Flexibility → Math readiness → 1st G. academic	−.188	.079	−.343	−.032	.018
CoV → Flexibility → Reading readiness → 1st G. academic	−.073	.052	−.175	.029	.161

Note: Est. = Unstandardized estimate; CoV = Coefficient of Variation; flexibility = cognitive flexibility; 1^{st} G. academic = 1^{st} grade academic performance