Executive functions and science achievement during the five-to-seven-year shift

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Abstract

Executive functions (EF) are domain-general cognitive skills that predict school success. However, less is known about the relation between EFs and science achievement. The present study examined the bidirectional associations between science achievement and children's cognitive flexibility and working memory in a nationally representative sample of children in the United States (ECLS-K: 2011; $N = 18,174$). Using random intercepts cross-lagged panel modeling, results revealed a heterogeneous pattern of associations between EF and science achievement. Trait-like and construct stability emerged in the between-person and within-person estimates of EF and science. Cognitive flexibility and working memory in kindergarten each predicted science achievement in first grade. Science achievement in the fall of first grade predicted cognitive flexibility in the spring of first grade. There were also bidirectional associations between working memory and science achievement in the fall and spring of first grade. Findings from the current study reveal the complex interplay between EF and science achievement during early childhood and highlight the potential of boosting science competencies to promote growth in cognitive skills important for goal-directed activity during early schooling.

Keywords: Executive Functions, Cognitive Flexibility, Working Memory, Science Achievement, Early Childhood

Introduction

Research on the interplay between executive function (EF) and early academic achievement has largely centered on reading and math achievement (Best et al., 2011; Clark et al., 2010; Fuhs et al., 2014; McClelland et al., 2014). However, a body of research is beginning to emerge regarding the association between EF and science in preschool (Bustamante et al., 2017; Nayfield et al., 2013) and the early elementary grades (Anthony & Ogg, 2019; Morgan et al., 2018). During this developmental period, often called the “five-to-seven-year shift,” children across cultures develop increasingly sophisticated cognitive and social capacities (Sameroff & Haith, 1996). As children acquire a greater understanding of the world, they also develop schemas that allow them to learn about and understand scientific concepts. Building models, testing hypotheses, and revising theories are inherent to the scientific method. These skills closely reflect and may depend on EF skills of cognitive flexibility, inhibitory control, and working memory (Gropen et al., 2011). Accordingly, the development of EF skills may enhance science achievement. However, it is also possible that the development of early science competencies may promote growth in EF. Because achievement gaps in science emerge as early as kindergarten (Morgan et al., 2016), it is important to gain a better understanding of the factors that influence the development of early science competencies. In the present study, we use longitudinal, nationally representative data from the United States to examine the autoregressive and cross-lagged associations between EF and science achievement in kindergarten and first grade.

Executive functions

Children’s cognitive abilities undergo profound changes during the five-to-seven-year shift (Sameroff & Haith, 1996). Of particular interest is children’s cognitive self-regulation, often referred to as executive functions (EF). Early childhood is characterized by individual differences

underlying rapid growth in EF (Montroy et al., 2016; Zelazo & Carlson, 2012). While the componential nature of EF in young children during this developmental period remains a topic of discussion, evidence generally supports the view that EF is best understood as comprising multiple distinct but partially overlapping constructs of cognitive flexibility, inhibitory control, and working memory (e.g., Ahmed, 2019; Hughes et al., 2009; Wiebe et al., 2011).

The capacities to shift attention between tasks (cognitive flexibility), controlling and withholding one's responses (inhibitory control), and to keep multiple facets of information in mind while engaging in other activities (working memory), have been linked to academic success across childhood and adolescence (Blair, 2016; Diamond, 2012). Preschool EF skills are positively associated with early math achievement (Clark et al., 2010), and longitudinal analyses demonstrate that EF components strongly predict math and reading growth during the kindergarten year (Fuhs et al., 2014). In a sample of children living in rural areas in the United States, EF skills at age five were linked to better academic skills in fifth grade (Ribner et al., 2017). Research has identified working memory in particular as a strong predictor of later achievement. In a study examining the transition to first grade, working memory in kindergarten emerged as the only EF component that predicted first grade spelling and math achievement (Vandenbroucke et al., 2017). In a separate study, working memory at 54 months was shown to significantly predict math and reading achievement at 15 years of age (Ahmed et al., 2019).

While research has demonstrated that strong EF skills are related to early literacy and numeracy skills, gaps in EF skills explained by racial and socioeconomic differences exist as early as school entry. Gaps in children's cognitive flexibility and working memory appear to narrow as children progress through the early elementary grades, but they do not close completely (Little, 2017). Therefore, it is important to better understand whether other avenues for early intervention

could help reduce these gaps as early in schooling as possible. In this paper, we propose that examining children's early science competencies might broaden our understanding of EF development during the early elementary grades.

Science

The predominant focus on reading and math instruction in early childhood has masked the early learning that takes place in academic domains such as science. Our understanding of the nature and development of science learning and instruction has shifted in recent years, moving away from the belief that only older students possessed the capacity to participate in scientific reasoning and thinking (Cuevas et al., 2005; National Research Council, 2013). Just as EF is conceptualized as comprising three dimensions, science ability can also be understood as a multidimensional construct that encompasses two distinct but overlapping abilities—content knowledge and domain-general inquiry skills. Content knowledge relates to the *what* of science (i.e., factual information about the natural world), whereas domain-general inquiry skills relate to the *how* of science (e.g., designing experiments, drawing conclusions from evidence). Even very young children engage in abstract thinking, causal reasoning, and statistical learning, competencies that are associated with the development of scientific inquiry skills (Hadani & Rood, 2018).

Children enter school with their own preconceived ideas—or intuitive theories—about how the world works. Depending on students' backgrounds and experiences prior to school, their beliefs come from a variety of sources, including their parents, preschool activities, informal science experiences, and their own observations (Duschl et al., 2007). Due to the emerging cognitive capacities of children during this developmental period, children's rudimentary knowledge of science is incomplete and often includes errors and misconceptions. As children become engaged in formal science education, they are exposed to new ideas and evidence that

counters original misconceptions, resulting in the development of conceptual change, an important precursor to scientific thinking and understanding (Kuhn, 2002). Recent theorizing explicitly points to the contributions of executive functions, inhibition, and memory processes in shaping conceptual change (Vaughn et al., 2020).

Until recently, most of the existing literature on science achievement and interventions has been focused on older student populations, presumably because secondary schooling is when students typically begin to prepare for specialized academic and career pathways in science. Indeed, science content is typically not taught in a systematic way nor assessed using standardized measures until the later elementary years (Blank, 2013). However, children's engagement—or lack thereof—in science might shape later achievement trajectories. In studies investigating the onset of initial interest in STEM, individuals pursuing STEM-related career pathways frequently report that the early childhood and elementary years were critical to stimulating the interest that led to continued engagement with STEM activities (Maltese et al., 2014). Recent studies have also highlighted significant science achievement gaps, particularly by race/ethnicity, that not only are detectable in kindergarten (Morgan et al., 2016), but actually widen between kindergarten and first grade (Curran & Kellogg, 2016). Therefore, examining the nature of science abilities in early childhood might be the key to unlocking a fuller understanding of children's academic and cognitive skill development during the first few years of formal schooling.

Relating EF and science

Given the introduction of the Next Generation Science Standards (National Research Council, 2013), reforms in science education are moving away from teaching content-based knowledge to developing domain-general inquiry skills such as critical thinking, reasoning, and problem solving. A body of research demonstrates that educational experiences can improve

reasoning ability (Bunge & Leib, 2020), and experimental work has shown that teaching critical thinking can foster strong skills that are essential to all scientific disciplines (Holmes et al., 2015). Perhaps mirroring this trend, researchers are beginning to examine whether and how cognitive skills such as EF are associated with—or even predict—early science competencies.

The ability to test and revise hypotheses—a core science competency—may depend on EF capacities to represent and reflect on hierarchical rules that relate actions to outcomes (Gropen et al., 2011). This theory argues that children must be able to reconcile their actual observations of a particular phenomenon with their predictions of what would happen. That is, children must learn how to assimilate new data in order to accurately revise their understanding of the natural order, even if it seems counterintuitive to them. This scientific process of hypothesis testing and revision involves EF skills. Children need to flexibly shift their understanding when faced with new information (cognitive flexibility), rather than persevere in their original, incorrect understanding (inhibitory control). Children also need to be able to keep multiple facts in mind while revising their hypotheses (working memory). In elementary classrooms, children may be asked to make simple predictions (What do you think is going to happen?) and revisit these predictions based on their observations (What actually happened? Was your prediction right or wrong?). A body of research has demonstrated links between working memory and science learning and achievement, but many of these studies have focused on older children and adolescent youth (e.g., Yuan et al., 2006).

A number of studies have recently examined different aspects of this association in young children using data from the Early Childhood Longitudinal Study: Kindergarten Class of 2011 (ECLS-K:2011). Using OLS regression, Morgan and colleagues revealed that different components of EF (cognitive flexibility, inhibitory control, and working memory) assessed in

kindergarten predicted reading, math, and science achievement in second grade (Morgan et al., 2018). A separate study using growth curve modeling and mediation models demonstrated that learning-related behaviors mediate the relation between EF (cognitive flexibility and working memory) and science between kindergarten and fourth grade (Anthony & Ogg, 2019).

Research has typically examined how domain-general cognitive skills are predictive of academic outcomes. However, there has been far less attention on whether improving academic competencies might in turn enhance cognitive skills. We argue that the reverse relation might also be true—that is, strong scientific ability might predict EF skills. In the present study, we examine whether academic skills and psychological processes are *bidirectionally related* as a function of development. The theory of mutualism, broadly construed, posits that development is a complex system of interactive processes, in which the development of skills in one domain can also influence the development of skills in another domain (van der Maas et al., 2006). While this theory has been primarily considered in studies of intelligence, research has begun to examine the application of this theory to other areas of psychology, including whether academic abilities predict EF skills (Clements et al., 2016). A recent review of research reveals that academic skills (namely, reading and math) and cognitive abilities predict each other in development, and that direct academic instruction can improve reasoning skills (Peng & Kievit, 2020). We surmise that bidirectional pathways are also plausible in the context of science learning. While EF skills might predict better science outcomes, it is possible that participating in science learning activities can uniquely promote inquiry and hypothesis testing skills that in turn promote EF skills. Despite a strong theoretical rationale underlying this hypothesis, there does not yet exist empirical evidence indicating whether science abilities can uniquely predict EF skills. The present study applies modern advances in cross-lagged panel modeling, which is well suited to examining bidirectional

associations between EF and science across time, to examine the extent to which mutualism theory can be applied in the context of EF and science skill growth.

Study aims and hypotheses

The present study seeks to contribute new insights into the relation between EF and academic achievement in four distinct ways. First, by specifically examining science learning and achievement, we go beyond the dominant conceptualization of early academic skills as comprising literacy and numeracy. In fact, we argue that the process of science learning—which involves conceptual change and hypothesis testing and revision—may be uniquely suited to building EF skills. Second, we examine science achievement data that incorporates domain-general inquiry skills as well as content knowledge in order to gain a more comprehensive understanding of the nature and growth of early science competencies. Third, we examine these skills in a specific developmental period—the five-to-seven-year shift—during which children across cultures develop increasingly sophisticated cognitive and social capacities. Examining how growth in EF and science interact during the first years of formal schooling can inform hypothesis generation to examine the interaction of these skills further in time. Fourth, and perhaps the most distinct contribution of the present study, we examine whether academic skills (i.e., science ability) and psychological processes (i.e., executive functions) are bidirectionally related as a function of development.

In this study, we extend previous work by examining the bidirectional effects between early EF and science achievement during the critical developmental period known as the five-to-seven-year shift. Specifically, using random intercepts cross-lagged panel modeling, we examined the relative autoregressive and bidirectional effects between EF and children's science achievement. In keeping with the discipline's growing emphasis on understanding psychological processes in

diverse populations, we use a large, nationally-representative data set from the ECLS-K:2011 to examine the autoregressive and cross-lagged associations between two directly-assessed components of EF—cognitive flexibility and working memory—and science achievement in kindergarten and first grade. Based on empirical research linking EF with later academic achievement, we predicted that both cognitive flexibility and working memory would predict later science achievement. Based on the theoretical supposition of mutualism as well as empirical research demonstrating that academic skills and cognitive abilities can predict each other in development, we also hypothesized that science achievement would predict later cognitive flexibility and working memory skills.

Method

Participants

We examined public use data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010–2011 (ECLS-K:2011; $N = 18,174$), a prospective longitudinal study sponsored by the National Center for Education Statistics (NCES) within the Institute of Education Sciences of the U.S. Department of Education. Participants comprise a nationally representative sample of public and private school students, their families, teachers, schools and care providers (Tourangeau et al., 2015). The current study sample consists of children who were tested during the spring of kindergarten ($M_{age} = 73.4$ months old), fall of first grade ($M_{age} = 78.9$ months old), and spring of first grade ($M_{age} = 85.3$ months old). Because data were drawn from a publicly available, deidentified data set, approval from an Institutional Review Board was not obtained.

Participants in the ECLS-K:2011 come from diverse racial/ethnic backgrounds: 52% non-Hispanic White, 25% Hispanic, 13% African American, 5% Asian, 2% American Indian/Alaska Native or Native Hawaiian/Pacific Islander, and 4% two or more races. Children were split roughly

equally with respect to sex (49% female). Eighty-nine percent of students in this sample attended public school and 11% were enrolled in private school at the beginning of kindergarten. Approximately 8% of children had an individualized instruction program (IEP), and 16.2% of children came from homes where English was not the primary language spoken. This sample was also socioeconomically diverse; 26% of families were classified as being below the federal poverty line, 23% were between 100% and 200% of the poverty line, and 51% were above 200% of the federal poverty line. Further, 12% of primary caregivers reported completing less than a high school level education, 25% high school degree or equivalent, 33% some college or vocational training, and 29% bachelor's degree or higher. Sampling weights provided by NCES ensured that the final sample was representative of the U.S. population during the 2010-2011 school year.

Measures

Executive functions: Cognitive flexibility. Cognitive flexibility was measured using the Dimensional Change Card Sort (DCCS), a measure of cognitive flexibility where children are asked to sort a series of pictures by color, and then again by shape, and assesses children's ability to flexibly shift between different task rules (Zelazo, 2006). Two different versions of the DCCS were used in the ECLS-K:2011 study. In kindergarten and first grade, a hard copy version of the assessment was used, with children physically sorting the different cards into piles; performance was measured using the combined score that took into account sorting based on shapes, colors, and borders, as recommended by the ECLS-K technical manual (Tourangeau et al., 2018) and the task developers (Zelazo, 2006).

Executive functions: Working memory. The Numbers Reversed subtest of the Woodcock Johnson Tests of Achievement (WJ-NR) is a measure of working memory where children are presented with lists of numbers and are asked to repeat the numbers back in reverse

order (Mather & Woodcock, 2001). Students begin with five two-number sequences; if a student incorrectly repeats three consecutive two-number sequences, the assessment is discontinued. In each subsequent round, the number sequences increase by one digit, up to a maximum of eight-number sequences. The discontinue rule of three consecutive incorrect answers applies in each round, or until a student completes all number sequences. Scores were recoded into W scores; the W score metric is on an equal-interval scale and allows us to directly compare the achievement of one student against another, regardless of age (Jaffe, 2009).

Science achievement. The science assessment items used in the ECLS-K:2011 were chosen based on the areas identified by the National Assessment of Educational Progress (NAEP) as being key areas of elementary science knowledge. The four domains tested were scientific inquiry, physical science, life science, and Earth and space science. Each of these four domains were emphasized equally (i.e., 25% of items). Examples of items from the first and second grade assessments include interpreting data from observations (scientific inquiry), states of matter (physical science), functions of the human body (life science), and weather (Earth and space science; Najarian et al., 2018). Items were developed specifically for the ECLS-K:2011, obtained from a variety of non-copyrighted sources, and pulled from the K–4 assessments from the Peabody Individual Achievement Test–Revised. Due to data security requirements enforced by the National Center of Education Statistics, the wording of individual items is not readily obtainable.

The kindergarten science assessment included 20 items to which all children responded. In first grade, assessment involved a two-stage design that included a set of core questions in the first stage, and a separate set of questions in the second stage that depended on children’s responses in the first stage. All items in the science assessment were read aloud to children in order to ensure that reading ability did not affect their achievement on the science measure. Unfortunately, only

an overall science achievement score is available; scores for each science domain are not made available to researchers. Science achievement theta scores provided by NCES were used in the present analysis. Theta scores reflect overall measures of ability and are on the same metric across the kindergarten and first grade assessment time points. The distribution of theta scores is more normally distributed compared to scale scores, which is preferable for a multivariate analysis. Detailed information on measures and scoring can be found in Tourangeau et al. (2015).

Covariates. Children's demographic characteristics were obtained from interviews and parent and teacher questionnaires. Information regarding child's sex, age, guardian education level, occupation and primary language spoken at home was gathered from parents during interviews conducted in the fall of kindergarten, and household income was reported by parents during the spring kindergarten interview. Children's race and ethnicity was obtained through parent surveys and coded as White, non-Hispanic; Black, non-Hispanic; Hispanic; Asian; or Other. Household income included salary from all sources, interest, assets, and retirement, and was measured in 18 categories, ranging from \$5,000 or less to \$200,001 or more. Guardian education level was coded as highest grade or year of school completed ranging from 1st grade to doctorate or professional degree, and guardian occupation consisted of prestige scores from the General Social Survey of 1989 (Tourangeau et al., 2015). Socioeconomic status (SES) was represented by a composite score consisting of a) male guardian's education level; b) female guardian's education level; c) male guardian's occupation; d) female's guardian's occupation; and e) household income on a continuous scale ranging from -3.00 to 3.00, with larger values representing higher SES. Disability status was indicated by whether a child had an individualized education program (IEP), reported by special education teachers, filed at their school during kindergarten or first grade.

Longitudinal design

While the five-to-seven-year shift is typically understood to encompass kindergarten through second grade, we chose to focus our analysis on change across three time points in kindergarten and first grade—kindergarten spring (T1), first grade fall (T2), and first grade spring (T3). This decision was prompted by two features of the data set. First, we chose to focus only on the two dimensions of EF that were directly assessed at each time point—cognitive flexibility and working memory (inhibitory control was measured using a teacher report). The debate surrounding measurement approaches in EF research—particularly when considering direct assessments and teacher reports—has been well documented (e.g., Ahmed, 2019; McCoy, 2019; Toplak et al., 2013). Despite the predictive validity of teacher ratings of children’s EF on academic outcomes (e.g., Fuhs et al., 2015), teacher reports are often not characterized by the fine-grained specificity that permits an examination of discrete EF components. In addition, because teacher reports of inhibitory control were not administered during the fall of first grade, this would eliminate the possibility of a three-wave cross-lagged panel model.

Second, beginning in the second grade, a newly developed, computerized version of the DCCS was substituted for the physical cards, as the physical version of the DCCS was deemed too easy for students in second grade and older (Tourangeau et al., 2015). The computerized version of the DCCS incorporates more complex sorting rules across 30 trials of the assessment, and performance is measured by both sorting accuracy and reaction time. Accordingly, it is impossible to equate performance on the DCCS in kindergarten and first grade with DCCS performance in second grade. Previous studies that have examined the DCCS have addressed this limitation by implementing a regression analysis that does not depend on including DCCS scores across kindergarten/first grade and second grade waves (Morgan et al., 2018) or simply running a K-1 model for DCCS while running a K-2 model for working memory (Willoughby et al., 2019).

Accordingly, we decided to exclude second grade predictors and outcomes from our study in order to ensure the estimation of an analytical model that reflected a consistent measurement of EF across three time points in kindergarten and first grade.

Data analysis

Bidirectional associations between children's EF skills and science achievement were tested using a random intercepts, cross-lagged panel model (RI-CLPM; Hamaker et al., 2015). An extension of the standard CLPM, RI-CLPM not only allows for the estimation of autoregressive and cross-lagged regression parameters, but also permits the isolation of stable, between-person variance from time-varying, within-person variance. The inclusion of a random intercept accounts for time-invariant construct stability, permitting the examination of cross-lagged associations at the within-person level (Hamaker et al., 2015). In other words, RI-CLPM allows us to isolate the stable, between-person variation over time in both EF and science achievement in order to test bidirectional associations on the within-individual variation over time (Hamaker et al., 2015). The first step of the RI-CLPM includes extracting between-person factors from the repeated measures of cognitive flexibility, working memory, and science achievement by creating random intercepts and allowing them to covary. Next, autoregressive (i.e., rank-order construct stability) and cross-lagged paths (i.e., reciprocal associations) were estimated on the within-person centered factors, while covarying the within-person components (and innovation residuals) of cognitive flexibility, working memory, and science achievement at the first wave (Hamaker et al., 2015). Finally, we included demographic and child-level covariates (i.e., sex, age, SES, race/ethnicity, IEP status, and non-English home language) as predictors of the stable between-person factors (Mulder & Hamaker, 2020). See Figure 1 for full conceptual model.

Sampling weights

Sampling weights provided by NCES were applied to the analyses to ensure the data were representative of all children enrolled in kindergarten in the United States during the 2010-11 school year. The ECLS Electronic Codebook contains weighting schemes that are provided for analysis using data from each round of data collection and components (i.e., assessments and interview questionnaires). Consistent with best practices for examining developmental questions using secondary data (Davis-Kean et al., 2015); appropriate sampling weights for analysis were used. Specifically, the W4 (C1)(C2)(C4)(P1_P2)(P4)(T4) sampling weights that accounts for child, parent and teacher level data was used in the present study (Tourangeau et al., 2015).

Missing data

In addition to the stratified, multistage probability sampling design, the ECLS-K:2011 also included a planned missingness design to reduce field costs (Tourangeau et al., 2015). All study participants were assessed in the fall and spring of their kindergarten year, and each year (in the spring) thereafter ($N = 18,174$). However, a random subsample of the original participants was also assessed during the fall of first grade ($n = 6,040$). To account for the planned missingness across the current study's waves of interest (i.e., kindergarten spring, first grade fall, and first grade spring), missing data were imputed using multiple imputations (MI; Rubin, 1987) by chained equations procedures implemented in Mplus (Muthén & Muthén, 1998-2020) to create 40 complete data sets. Unlike listwise deletion, which can cause biased estimates, MI leverages all available data to estimate study parameters and standard errors and is considered highly effective in achieving unbiased regression estimates in the presence of planned and unplanned missing data (Davis-Kean et al., 2015; Little & Rhemtulla, 2013; Graham, 2003; Shin et al., 2009; Widaman, 2006). In this procedure, missing values are imputed based on the values and observed associations

for each individual and across all participants in the sample (Schafer & Graham, 2002). This technique allowed us to retain the full ECLS-K sample of 18,174.

Results

Descriptive statistics

Means, standard deviations, and range for main model indicators are presented in Table 1. Pearson's bivariate correlations are presented in Table 2. Concurrent correlations among EF measures were all significant ($p < .001$) within and across waves and were significantly related to science achievement in the spring of kindergarten and the fall and spring of first grade ($p < .001$).

Random-Intercepts, Cross-Lagged Panel Model

Figure 2 displays the findings from a three-wave RI-CLPM. The overall model demonstrated good model fit ($\chi^2 (69) = 508.5$, CFI = .99; TLI = .97; SRMR = .043; RMSEA = .019).

RI-CLPM Between-Person Findings. The standardized factor loadings for the between-person, random intercepts for science achievement ($\beta = .79 - .88$), working memory ($\beta = .65 - .74$), and cognitive flexibility ($\beta = .44 - .51$) were positive and statistically significant, suggesting varying levels of trait-like stability from kindergarten to first grade across constructs. Further, statistically significant random intercepts indicate that there were stable differences at the person-level means of science achievement, working memory, and cognitive flexibility over time. The positive covariances between the random intercepts suggest that on average, children with higher stability in working memory and cognitive flexibility had higher stability in their science achievement over time, and vice versa (see Figure 3 for standardized factor loadings and covariances for between-factor model).

RI-CLPM Within-Person Findings. Significant and small-to-moderate autoregressions across waves provided evidence of the within-person construct stability of science achievement ($\beta = .28 - .48$), working memory ($\beta = .08 - .19$), and cognitive flexibility ($\beta = .12 - .14$) from kindergarten to first grade (see Figure 4). After accounting for the construct stability of the model indicators, we observed significant and positive cross-lagged relations between working memory at T1 and cognitive flexibility at T2 ($\beta = .09$, $SE = .03$, $p < .001$) as well as cognitive flexibility at T1 and working memory at T2 ($\beta = .06$, $SE = .03$, $p < .001$). This reciprocal pattern supports the bidirectional nature of associations among working memory and cognitive flexibility from the spring of kindergarten to the fall of first grade. Further, we observed significant and positive paths from working memory ($\beta = .15$, $SE = .02$, $p < .001$) and cognitive flexibility at T1 ($\beta = .08$, $SE = .02$, $p < .001$) to science achievement at T2, which suggests that working memory and cognitive flexibility at the spring of kindergarten prospectively predicted standardized science achievement scores during the fall of first grade. However, non-significant paths from science achievement at T1 to working memory ($\beta = .06$, $SE = .04$, $p = .08$) and cognitive flexibility ($\beta = .03$, $SE = .04$, $p = .47$) at T2 points to a unidirectional relation between EF and science achievement from the spring of kindergarten to the fall of first grade.

A different pattern of directionality from T2 to T3 emerged. Specifically, working memory at T2 prospectively predicted cognitive flexibility at T3 ($\beta = .08$, $SE = .03$, $p < .001$), and not vice versa ($\beta = .05$, $SE = .03$, $p = .18$), indicating a unidirectional relation between working memory and cognitive flexibility from the fall to spring of first grade. We also observed a unidirectional pattern of association between science achievement at T2 and cognitive flexibility at T3. Specifically, science achievement at the fall of first grade prospectively predicted cognitive flexibility ($\beta = .07$, $SE = .03$, $p < .001$) at the spring of first grade and not vice versa ($\beta = .03$, SE

= .02, $p = .19$). Lastly, science achievement at T2 predicted working memory at T3 ($\beta = .10$, $SE = .03$, $p < .001$) and working memory at T2 predicted science achievement at T3 ($\beta = .08$, $SE = .02$, $p < .001$), suggesting that science achievement and working memory were reciprocally related across the fall and spring of first grade (see Figure 5 for within-person, cross-lagged regression coefficients). Figure 6 presents the full RI-CLPM displaying all between and within model coefficients.

Discussion

The purpose of the present study was to examine the bidirectional associations between executive functions and science achievement in a nationally representative sample of kindergarten and first grade students. We estimated a random intercepts cross-lagged panel model that included two EF components—cognitive flexibility, and working memory—and science achievement. Results revealed a complex pattern of associations between EF components across time, as well as unidirectional and bidirectional associations between EF and science. Four primary results emerged: (1) There was trait-like stability in the between-person estimates of cognitive flexibility, working memory, and science achievement. (2) Cognitive flexibility and working memory in kindergarten each prospectively predicted science achievement in first grade. (3) Science achievement in the fall of first grade prospectively predicted cognitive flexibility in the spring of first grade. (4) Bidirectional associations emerged between working memory and science achievement in the fall and spring of first grade.

Between-person findings for EF and science

A notable strength of RI-CLPM is its ability to separate between-person from within-person effects, thereby permitting a more precise understanding of the nature of the association between EF and science. Specifically, the inclusion of a random intercept allows us to test whether

EF and science performance are influenced by individual and/or contextual factors that are stable over time (Hamaker et al., 2015). We found that both EF and science achievement exhibited trait-like stability from kindergarten to first grade, suggesting that there are unmeasured stable factors influencing performance on these constructs over this period of time (Bailey et al., 2020). Further, the observed covariances among the EF and science random intercepts suggests that stability in science performance over time was related to stability over time in working memory and cognitive flexibility, and vice versa. That is, children who had larger over time means in science achievement also exhibited larger over time means for cognitive flexibility and working memory.

This overlap in between-person stability estimates is consistent with recent work examining bidirectional associations between math and reading using a RI-CLPM (e.g., Bailey et al., 2020). These findings also provide additional insight into the mutualistic development of cognitive and academic domains during early childhood (Peng & Kievit, 2020), and have implications for identifying students at-risk for academic difficulties. For example, the longitudinal overlap in the stability estimates for science and EF can suggest that children who struggle in one domain may also have difficulties in the other domain (e.g., Bailey et al., 2020; Cirino et al., 2018). However, this approach does not offer insight into the sources of stability—that is, whether the unmeasured stable factors in EF and science are explained by individual or contextual influences that are stable over time. As noted by Bailey and colleagues (2020), a promising future direction in this area would be to identify the time invariant factors that underlie the longitudinal relations across academic and cognitive domains.

Within-person associations between EF and science

After controlling for the between-person effects and the within-person autoregressive estimates, results revealed significant positive bidirectional cross-lagged relations between

working memory and cognitive flexibility between the spring of kindergarten and the fall of first grade at the within-person level. We also found that working memory in the fall predicted cognitive flexibility in the spring, but not vice versa. In particular, it appears that working memory is a reliable predictor of later cognitive flexibility, although the evidence for the other direction is less conclusive. Importantly, these effects were small but consistently sized (between .06 and .09 SD units). Future research should examine whether and how these associations between EF components evolve beyond first grade; an examination of direct assessments of inhibitory control would also provide greater insights into the dynamic interplay between these discrete EF components throughout the elementary school years.

We also found that working memory and cognitive flexibility in the spring of kindergarten prospectively predicted science achievement in the fall of first grade. However, the path from science to either EF component was close to zero, indicating a unidirectional association between EF and science from kindergarten to first grade. Conversely, we found a unidirectional relation between science achievement and cognitive flexibility across first grade, such that science achievement in the fall prospectively predicted cognitive flexibility in the spring, but not vice versa. One potential explanation for these results might relate to what is occurring during the summer between kindergarten and first grade. A large body of research has sought to characterize the growth—or lack thereof—in children’s academic skills during the summer months, with evidence for (e.g., Alexander et al., 2007) and against (e.g., von Hippel & Hamrock, 2019) the idea of summer learning loss. Recently, attention has focused on whether and how the summer months impact children’s growth in behavioral and cognitive skills. Findings from a recent study demonstrate that working memory skills grow more during the school year compared to the summer months (Finch, 2019). Accordingly, differences in the growth trajectories in academic

(i.e., science) and EF skills during the school year and the summer months, combined with the timing of assessments, may explain our findings. However, without information regarding the summer experiences of children, it is difficult to pinpoint the mechanisms driving these different unidirectional associations. Children who participate in summer science camps or other programs that allow children to grow their EF skills through modeling and practice, might develop these competencies more strongly than children who do not have such opportunities. Collecting and integrating data on children's summer experiences into our analytical models would be an important direction for future research.

Bidirectional associations between EF and science

Perhaps due to the growing accountability pressures faced by school districts, the predominant focus in elementary schools in the United States is to improve academic skills and outcomes. Therefore, many empirical studies are often framed against an examination of whether and how domain-general cognitive skills can be developed in service of enhanced academic achievement, rather than also considering whether and how developing academic skills can also improve domain-general skills. Our results not only add to the growing body of literature demonstrating that executive functions predict later academic achievement, but also revealed that promoting science competencies—which include both content knowledge and scientific inquiry skills—can promote EF skills. While much of this work has focused on literacy and numeracy, the present study extends this understanding by examining the relation between EF and science achievement.

In our data, we did not observe any bidirectional associations between spring of kindergarten and fall of first grade. However, when examining relations from fall to spring of first grade, science achievement in the fall predicted working memory in the spring, and working

memory in the fall predicted science achievement in the spring, indicating that both science and working memory are reciprocally related during first grade. Our findings lend support for the theory of mutualism by revealing bidirectional associations between cognitive abilities and academic achievement (Peng & Kievit, 2020), and to demonstrate that this association applies not only to reading and math but also elementary science learning.

Our findings showing that working memory—instead of cognitive flexibility—was more strongly linked to academic skills are consistent with research in other academic domains (such as math) indicating the stronger predictive power of working memory skills over cognitive flexibility and inhibitory control in predicting later achievement (e.g., Bull & Lee, 2014). However, it is important to note that other studies have also found impacts of cognitive flexibility and inhibitory control (e.g., Anthony & Ogg, 2019; Morgan et al., 2018) on later science achievement, in addition to impacts of working memory. One interpretation of these findings, when considered collectively, is that the nature of the relation between particular dimensions of EF and science differs as a function of grade level. We only examined kindergarten and first grade children, while the aforementioned studies examined children through second grade (Morgan et al., 2018) and fourth grade (Anthony & Ogg, 2019). Perhaps working memory is a stronger predictor of science abilities during the earliest schooling years, with other EF components such as cognitive flexibility and inhibitory control emerging as separate predictors in their own right as children continue to develop. Supporting this claim is research demonstrating that working memory exhibits the largest rates of change in childhood and adolescence compared to other higher-order cognitive abilities (Gur et al., 2012). The protracted course of development in working memory skills might explain why stronger early performance in this particular domain might be a more reliable predictor of later academic skills compared to other EF domains. This hypothesis should be tested in future

research.

The potential role of science instruction

When considering the link between science achievement and later EF skills, questions surrounding the nature and timing of early science instruction become important to consider. However, due to the wide variability in state standards and implementation, a clear picture of science instruction in early elementary school remains elusive. Despite the four separate domains that were tested in the ECLS-K, it is likely that science instruction in the early elementary grades is not particularly differentiated across specific scientific domains, and even if they are, it is unclear the extent to which children find these distinctions to be obvious or meaningful. However, as students become increasingly able to understand different scientific concepts and ideas across different scientific domains as children mature cognitively, the nature, type, and duration of science instruction is likely to evolve as children progress through the elementary grades and beyond. For example, science instruction in kindergarten might focus on simple concepts such as gravity and different states of water, while instruction in later elementary school might focus more heavily on inquiry skills, such as how to test a hypothesis by controlling and manipulating variables. Our cross-lagged results indicate that science achievement predicts not only future science achievement, but also EF skills. Therefore, it would be instructive to examine whether and how science instruction and knowledge in inquiry and content domains during early elementary school shapes—and is shaped by—early EF. Further, because science is not formally tested in most elementary schools until fourth or fifth grade, understanding whether and how standardized testing incentivizes or disincentivizes certain instructional emphases and strategies is of profound interest. As the ECLS-K:2011 continues to release data at later time points, there will be increased opportunities to examine more complex developmental questions across wider time points that

model change at multiple levels—person, family, classroom, and school.

Limitations and future directions

The limitations of the present study also point to specific directions for future research. First, due to the nature of the data set, we were not able to obtain the wording of individual items as well as subscale scores for the science assessment used in the ECLS-K:2011. As described earlier, the science assessment included questions in four separate, equally represented domains: Scientific inquiry, physical science, life science, and Earth and space science. Unfortunately, researchers are only allowed access to a broad description of the items in each domain and the overall scale score. This “black box” makes it impossible to determine whether our findings are attributable to either scientific content knowledge (representing 75% of the items in the scale) or scientific inquiry skills (representing 25% of the items in the scale), or a combination of both. Despite the national and global interest in preparing young students to enter productive, well-paying careers in STEM fields, this data restriction severely limits our ability to examine more nuanced questions regarding the nature and growth of children’s science achievement in elementary school. With the continued growth and acceptance of open science practices in developmental and educational science (Davis-Kean & Ellis, 2019; van der Zee & Reich, 2018), we call on the field to help promote greater replicability by increasing access to data and materials.

Second, while we demonstrated that science achievement can predict later EF skills, we were not able to examine the classroom and instructional mechanisms that might underlie this effect. These mechanisms may be related to mode of instruction (e.g., child-centered vs. teacher-centered; Neitzel & Connor, 2014), instructional time devoted to science (Curran & Kitchin, 2019), as well as the structural organization of classrooms unrelated to content instruction (Morrison et al., 2019). Decisions about how instructional time is allocated across different learning domains

can also influence achievement. Much of the available data on science instructional practices are based on teacher reports of their use of instructional strategies and content areas covered. Smaller-scale studies that include classroom observations and qualitative inquiry into the nature, format, quality, duration of actual science instruction, and the student learning experience can yield detailed information to supplement the quantitative findings from the present study. Observational methods that could better characterize the quality of instruction and effective use of promising practices, as well as documenting specific successes and challenges to elementary science education, would benefit researchers and educators alike.

Third, while states historically have set heavily content-based science standards for each grade level, control over when and how the standards are taught has often remained at the district or even building and classroom levels, resulting in wide variation of implementation of elementary science instruction. Although the recently adopted Next Generation Science Standards (NGSS) were developed to improve and update science education using research-based standards and practices, as of today, only 20 U.S. States and the District of Columbia have adopted the NGSS; thus, there is no generally accepted standard of coherence for the delivery of science instruction at the elementary level. While an examination of a nationally representative sample of children is a strength of the present study, this broad generalizability also masks significant state- and district-level policy differences that influence how science is instructed. Future studies that systematically examine the role of state and local policies on teacher practice and subsequent student learning would supplement the current findings.

Conclusion

In a nationally representative sample of kindergarten and first grade children, unidirectional and bidirectional associations emerged between executive functions and science

achievement. We found trait-like stability in the between-person estimates of cognitive flexibility, working memory, and science achievement. Cognitive flexibility and working memory in kindergarten each predicted science achievement in first grade. Science achievement in the fall of first grade prospectively predicted cognitive flexibility in the spring of first grade. There were bidirectional associations between working memory and science achievement in the fall and spring of first grade. These findings point to the bidirectional association between academic and cognitive skills in early childhood and extend previous work by demonstrating the unique, predictive value of early science competencies on growth in domain-general cognitive skills such as EF. Future studies should seek to examine the instructional mechanisms that underlie this effect, as well as examine these associations later in elementary school.

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Table 1*Unimputed Means, Standard Deviations, Sample Size and Range for Model Indicators*

Variable	N	M	SD	Min	Max	%Missing
Time 1						
Science Achievement	16940	-.61	.74	-2.65	.99	6.8%
Working Memory	17150	449.68	30.52	393	572	5.6%
Cognitive Flexibility	17150	15.14	2.80	0.00	18	5.6%
Time 2						
Science Achievement	5180	-.46	.87	-3.08	1.82	*14.2%
Working Memory	5220	456.96	28.74	393	596	*13.6%
Cognitive Flexibility	5220	15.70	2.44	0.00	18	*13.6%
Time 3						
Science Achievement	15070	1.0	.81	-2.96	1.96	17.1%
Working Memory	15110	469.33	25.82	393	596	16.8%
Cognitive Flexibility	15110	16.05	2.31	0.00	18	16.8%

Note. Sample sizes rounded to nearest 10 per National Center for Education Statistics requirement.

Sample size for all variables are prior to Multiple Imputation

Time 1 = Spring of Kindergarten, Time 2 = Fall of First Grade, Time 3 = Spring of First Grade

*%Missing for Time 2 variables calculated out of full random subsample at fall of first grade ($n = 6040$) and represents percentage of unplanned missingness due to attrition

Science Achievement = IRT-Based Theta Score

Working Memory = W Score of Numbers Reversed Test (Mather & Woodcock, 2001)

Cognitive Flexibility = Combined score of the Dimensional Change Card Sort (Zelazo, 2006)

Table 2*Correlations for Main Study Variables*

	1.	2.	3.	4.	5.	6.	7.	8.	9
Time 1									
1. Science Achievement	-								
2. Working Memory	.48	-							
3. Cognitive Flexibility	.33	.30	-						
Time 2									
4. Science Achievement	.80	.48	.35	-					
5. Working Memory	.40	.57	.29	.46	-				
6. Cognitive Flexibility	.31	.30	.32	.36	.31	-			
Time 3									
7. Science Achievement	.77	.49	.35	.85	.46	.35	-		
8. Working Memory	.38	.52	.27	.42	.55	.28	.46	-	
9. Cognitive Flexibility	.31	.28	.27	.32	.28	.33	.37	.31	-

Note. Bold = $p < .001$ level.

Time 1 = Spring of Kindergarten, Time 2 = Fall of First Grade, Time 3 = Spring of First Grade

Science Achievement = IRT-Based Theta Score

Working Memory = W Score of Numbers Reversed Test (Mather & Woodcock, 2001)

Cognitive Flexibility = Combined score of the Dimensional Change Card Sort (Zelazo, 2006)

Figure 1*Conceptual Random Intercepts, Crossed Lagged Panel Model*

Note. bSci, bWM, and bCF are stable between-person random intercepts extracted from the repeated measures of science achievement, working memory, and cognitive flexibility, respectively.

wSci, wWM, and wCF are within-person centered factors extracted from each timepoint.

Covariates (i.e., sex, age, SES, race/ethnicity, IEP status, and non-English home language) are predictors of the stable between-person factors.

Figure 2*RI-CLPM Results (N = 18,174)*

Model fit statistics: $\chi^2(69) = 508.5$, CFI = .99; TLI = .97; SRMR = .043; RMSEA = .019

Note. Solid lines represent significant standardized paths coefficients at the $p < .01$ level.

bSci, **bWM**, and **bCF** are stable between-person random intercepts extracted from the repeated measures of science achievement, working memory, and cognitive flexibility, respectively.

wSci, **wWM**, and **wCF** are within-person centered factors extracted from each timepoint.

Covariates (i.e., sex, age, SES, race/ethnicity, IEP status, and non-English home language) are predictors of the stable between-person factors.

Missing data were imputed using multiple imputations by chained equations procedures to create 40 complete data sets.

ECLS-K sampling weights that accounts for child, parent and teacher level data included in this model.

MLR estimator - maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic.

Figure 3

RI-CLPM Results: Standardized Factor Loadings and Covariances for Between-Factor Model (N = 18,174)

Model fit statistics: $\chi^2(69) = 508.5$, CFI = .99; TLI = .97; SRMR = .043; RMSEA = .019

Note. bSci, bWM, and bCF are stable between-person random intercepts extracted from the repeated measures of science achievement, working memory, and cognitive flexibility, respectively.

wSci, wWM, and wCF are within-person centered factors extracted from each timepoint.

Covariates (i.e., sex, age, SES, race/ethnicity, IEP status, and non-English home language) are predictors of the stable between-person factors.

Missing data were imputed using multiple imputations by chained equations procedures to create 40 complete data sets.

ECLS-K sampling weights that accounts for child, parent and teacher level data included in this model.

MLR estimator - maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic.

Figure 4

RI-CLPM Results: Within-Person Autoregression and Within-Wave Regression Coefficients (N = 18,174)

Model fit statistics: $\chi^2(69) = 508.5$, CFI = .99; TLI = .97; SRMR = .043; RMSEA = .019

Note. Solid lines represent significant standardized paths coefficients at the $p < .01$ level.

bSci, bWM, and bCF are stable between-person random intercepts extracted from the repeated measures of science achievement, working memory, and cognitive flexibility, respectively.

wSci, wWM, and wCF are within-person centered factors extracted from each timepoint.

Covariates (i.e., sex, age, SES, race/ethnicity, IEP status, and non-English home language) are predictors of the stable between-person factors.

Missing data were imputed using multiple imputations by chained equations procedures to create 40 complete data sets.

ECLS-K sampling weights that accounts for child, parent and teacher level data included in this model.

MLR estimator - maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic.

Figure 5

RI-CLPM Results: Within-Person Cross-Lagged Regression Coefficients (N = 18,174)

Model fit statistics: $\chi^2(69) = 508.5$, CFI = .99; TLI = .97; SRMR = .043; RMSEA = .019

Note. Solid lines represent significant standardized paths coefficients at the $p < .01$ level.

bSci, bWM, and bCF are stable between-person random intercepts extracted from the repeated measures of science achievement, working memory, and cognitive flexibility, respectively.

wSci, wWM, and wCF are within-person centered factors extracted from each timepoint.

Covariates (i.e., sex, age, SES, race/ethnicity, IEP status, and non-English home language) are predictors of the stable between-person factors.

Missing data were imputed using multiple imputations by chained equations procedures to create 40 complete data sets.

ECLS-K sampling weights that accounts for child, parent and teacher level data included in this model.

MLR estimator - maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic.

Figure 6

RI-CLPM Results: Full Model Displaying all Between and Within Model Coefficients (N = 18,174)

Model fit statistics: $\chi^2(69) = 508.5$, CFI = .99; TLI = .97; SRMR = .043; RMSEA = .019

Note. Solid lines represent significant standardized paths coefficients at the $p < .01$ level.

bSci, bWM, and bCF are stable between-person random intercepts extracted from the repeated measures of science achievement, working memory, and cognitive flexibility, respectively.

wSci, wWM, and wCF are within-person centered factors extracted from each timepoint.

Covariates (i.e., sex, age, SES, race/ethnicity, IEP status, and non-English home language) are predictors of the stable between-person factors.

Missing data were imputed using multiple imputations by chained equations procedures to create 40 complete data sets.

ECLS-K sampling weights that accounts for child, parent and teacher level data included in this model.

MLR estimator - maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic.