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Research paper

Unique and compensatory associations of executive functioning and visuomotor integration with mathematics performance in early elementary school

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ABSTRACT

Research has illuminated contributions—usually modeled separately—of both executive functioning (EF) and visuomotor integration (VMI) to mathematical development in early elementary school. This study examined simultaneous associations of EF and VMI, measured at the beginning of the school year, with concurrent and later mathematics performance on several mathematics assessments in kindergartners (n = 89, M_{age} = 5.5 years) and first graders (n = 73, M_{age} = 6.6 years) of low socioeconomic status. Both skills were related to concurrent performance on all assessments, as well as improvement through the end of the school year for all but a geometry subtest, which was predicted only by VMI. No significant influence of an interaction between the skills was present, except for concurrently on the geometry subtest and longitudinally on an assessment with a relatively strong emphasis on informal skills. Findings are discussed in the context of supporting mathematics development in early childhood.

1. Introduction

Children's early mathematics ability is an important factor supporting academic success (e.g., Duncan et al., 2007), but other less explicitly academic skills, when measured in early childhood, are also strongly associated with later academic outcomes (Heckman, Stixrud, & Urzua, 2006). Executive functioning (EF) and visuomotor integration (VMI) upon school entry are two such skills, especially in the way they support mathematics learning (Cragg & Gilmore, 2014; Verdine, Irwin, Golinkoff, & Hirsh-Pasek, 2014). Each of these skills shows consistent associations with later mathematics outcomes (e.g., Blair & Razza, 2007; Newcombe & Frick, 2010) and theory has independently been developed for each skill regarding why each might support academic achievement and mathematics achievement in particular. However, despite these skills appearing to co-develop in early childhood (see Cameron, Cottone, Murrah, & Grissmer, 2016), studies linking them to mathematics performance have often considered them in isolation. Thus, whether each skill makes a unique contribution to mathematics performance when the other is measured is less well understood, as is whether strengths in one skill might compensate for relative weaknesses in the other. Even less understood is whether such contributions are consistent across different types of mathematics assessments.

Understanding the contributions of cognitive skills to academic outcomes may be especially important in populations with low socioeconomic status (SES; i.e., racial minority status and/or of low-income), who are traditionally considered at-risk for school difficulties. This heightened risk can, in part, be explained by fewer opportunities for children of low socioeconomic status to fully develop the cognitive skills which promote academic adjustment and performance (Bradley & Caldwell, 2013; Verdine, Golinkoff et al., 2014).

This study examines both EF and VMI as predictors of concurrent mathematics performance and improvement in several measures of mathematics performance over the course of one school year in a sample of mostly African-American kindergarteners and first graders from low-income families. Based on research with preschool-age children (Cameron et al., 2015), compensatory effects – by which strengths in one skill counteract effects of short-comings in the other – between EF and VMI were also tested.

1.1. EF and academic performance

EF is a cognitive construct typically described as the higher cognitive processes underlying conscious control of thought and action

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(Jacques & Marcovitch, 2010). These processes fall into correlated but distinct components: working memory, cognitive flexibility, and inhibitory control (Diamond, 2013; Miyake et al., 2000). In this study, EF was measured using a composite from multiple tasks.

Development in EF is characterized by several periods of rapid growth, particularly during early childhood (Diamond, 2006; Romine & Reynolds, 2005). Early overall EF, as well as specific components of EF, are linked to a wide range of academic and life outcomes from preschool through adulthood (Diamond, 2013; McClelland, Acock, Piccinin, Rhea, & Stallings, 2013). For instance, McClelland et al. (2007) found that incoming EF in preschool was correlated with initial academic skills but also predicted preschoolers' math and literacy improvements by the end of preschool. EF is also associated with academic achievement in math and literacy after children transition to kindergarten (Ponitz, McClelland, Matthews, & Morrison, 2009), even after controlling for IQ (Blair & Razza, 2007). The association between preschool EF and academic skills is consistent at least through college (Duncan et al., 2007; McClelland et al., 2013).

Beyond facilitating appropriate classroom engagement, EF supports specific academic tasks, especially in mathematics (Geary, 2011; Willoughby, Blair, Wirth, & Greenberg, 2012). For example, children with low inhibitory control − one component of EF − may be less likely to evaluate and switch mathematical problem-solving strategies when they prove ineffective (Bull & Scerif, 2001). EF seems to be particularly important for word problems, which require students to build and manipulate models of the problems in their heads (Fuchs et al., 2010a, 2010b).

Empirical evidence confirms that EF undergirds performance on mathematical tasks, with many studies demonstrating their concurrent and longitudinal links. For instance, both overall EF and specific components of EF are known to longitudinally predict mathematics performance in early childhood (Clark, Sheffield, Wiebe, & Epsy, 2013), early elementary school (Geary, 2011), and middle elementary school (LeFevre et al., 2013). Numerous studies demonstrate that EF, and especially working memory, accounts for significant variance in mathematics performance above and beyond other potential confounds, including prior mathematics performance, language skills, and even IQ (see Cragg & Gilmore, 2014 for a review). Recent studies have even suggested that EF may, at least partially, mediate the relationship between SES and mathematics outcomes (Dilworth-Bart, 2012) and researchers have suggested that promoting EF as part of encouraging children to develop adaptive self-regulatory strategies could be a viable means to improve the academic outcomes of children from low-SES families (Ursache, Blair, & Raver, 2012).

1.2. VMI and academic performance

VMI is considered an aspect of visuospatial processing and, like EF, is a complex process requiring integration of multiple skills, namely, visual and motor functioning (Beery & Buktenica, 1997). The most prominently used measures of VMI are design-copying tasks, in which individuals are typically asked to copy a series of increasingly complex figures. While copying a design may seem like a fairly simple task, it requires several component skills, chief among them the ability to parse a whole figure into its parts and to reintegrate those parts into a whole (Akshoomoff & Stiles, 1995).

The development of VMI, which is preceded by development of more rudimentary visual and motor skills prior to their integration develops rapidly during early childhood (ages 4 through 7 years), but continues through at least age 12 (Decker, Englund, Carboni, & Brooks, 2011). Past research drew attention to visuospatial skills in general, and VMI in particular, by documenting links between early "visuospatial" or "fine motor" skills and later academic achievement (e.g., Cameron et al., 2012; Carlson, Rowe, & Curby, 2013; Grissmer, Grimm, Aiyer, Murrah, & Steele, 2010; Luo, Jose, Huntsinger, & Pigott, 2007; Stevenson & Newman, 1986). These studies' measures often included design-copying tasks, which as mentioned above are elsewhere and in this study are considered measures of VMI (e.g., Beery & Buktenica, 1997, Korkman, Kirk, & Kemp, 1998). As discussed next, several studies document links of VMI with mathematics performance, specifically.

Developmental theory and research has long highlighted the notion that basic mathematical competencies (e.g., concepts of number) are directly dependent upon visuospatial development. Indeed, mathematical tasks in the classroom (e.g., estimating the number of objects in a jar, measuring the length of an object, copying diagrams from the board) often require visuospatial skills and VMI. Further, research in cognitive neuroscience points to a neural basis for the link between visuospatial skills and mathematical abilities. Dehaene and Cohen (2007) suggest that the neural machinery supporting humans' sophisticated visual spatial processing abilities may be "recycled" to form powerful visual representations of mathematical concepts (e.g., as in the development of a mental number line; Dehaene, 2011).

Empirical evidence has also documented links between visuospatial skills and mathematics development in children. In two studies of early elementary school students, one with a low-SES sample, and the other with a middle-SES sample, Gunderson, Ramirez, Beilock, and Levine (2012) found that children's visuospatial skills predicted later number line knowledge and calculation skills, even after controlling for prior number line knowledge and math ability. While these findings are what one might expect given work linking visuospatial skills with the mental number line in adults (e.g. Doricchi, Guariglia, Gasparini, & Tomaiuolo, 2005), it is also possible that EF was a confound in these relationships, as it was not measured. Although visuospatial skills and EF are distinct cognitive processes, any task that requires attentional resources and problem solving will also utilize EF (Korkman et al., 1998), and visuospatial skills tasks are no exception. Indeed, at least one study has found that the association between VMI and mathematics does not hold after controlling for certain measures of attention, which are considered an aspect of EF (Sortor & Kulp, 2003). Therefore, it is important to measure EF when examining visuospatial (and VMI) skills' unique contribution to early math skills, and vice versa. Further, because children from low-income households tend to have nascent visuospatial skills early in elementary school (Potter, Mashburn, & Grissmer, 2013), it may be particularly important to understand to what extent this ability contributes to mathematics performance in a sample of children from low-SES families.

1.3. Unique contributions of EF and VMI to mathematics performance

EF and visuospatial skills in general, and VMI in particular, may exhibit co-dependency in development and may interact in nuanced ways to support children's adaptation in school (Assel, Landry, Swank, Smith, & Steelman, 2003; Cameron et al., 2016). Ample evidence exists to support the notion that EF is an important promotive factor for school success and mathematics performance in particular, above and beyond other potential confounds, such as intelligence (see Cragg & Gilmore, 2014 for a review). Less research has focused on whether apparent contributions of visuospatial ability in general, and VMI in particular, to mathematics performance remain after accounting for other cognitive skills such as EF. Thus, while there is reason to suspect that EF should predict mathematics performance even when accounting for visuospatial skills, such as VMI, it is less clear that the converse is true (i.e., that VMI should predict mathematics performance after accounting for EF).

Two studies utilizing teacher reports for EF found unique associations between visuospatial skills and mathematics performance. Assel et al. (2003) measured visuospatial skills, in part, with a design-copying task and EF using teacher report at ages three, four, and six; and mathematics ability at age eight in low- to lower-middle-SES children. They found that both predictors were highly correlated from one time point to another (i.e., visuospatial skills to visuospatial skills and EF to EF) and that visuospatial skills and teacher-rated EF at age six were each uniquely associated with mathematics ability at age eight. The study did not include a measure of mathematical ability prior to age 8, however. Similarly, Grissmer et al. (2010) analyzed six nationally representative data sets, including ECLS-K, and found that age 5 measures of both VMI and teacher-reported EF predicted math ability in fifth grade, even after controlling for mathematics performance at kindergarten entry. Thus, both studies suggest that visuospatial skills are important above and beyond their relationship with EF, though measurement of EF in these studies was through teacher-report, which is conceptually different from directly-measured EF, as in this study.

Findings from research using *direct* measures of EF during the transition to formal schooling have sometimes, but not always, been consistent with research using teacher-reports, described immediately above. For example, in a small (n = 44), economically diverse sample of preschoolers, direct measures of both EF and visuospatial skills − including VMI − were uniquely related to concurrent mathematics (Verdine, Irwin et al., 2014). In slight contrast, Cameron et al. (2012) found in a middle- to upper-middle-SES sample that kindergarten-entry EF, but not VMI, was robustly associated with initial mathematics as well as to gains in mathematics. Sample demographics including age may explain these discrepancies: Cameron et al.'s (2012) sample was mostly middle- to upper-middle-class children who have, on average, stronger visuospatial skills at school entry than their lower SES peers (Potter et al., 2013). Thus, many of the children in the Cameron et al. (2012) study may already have had a level of visuospatial skills that readied them for kindergarten mathematics, which underscores the need for research examining the role of visuospatial skills in low-SES children. Finally, Becker, Miao, Duncan, and McClelland (2014) found both EF and VMI to predict later performance on applied problem solving mathematics assessment in an economically diverse sample of preschool and kindergarten-aged children. Verdine, Golinkoff et al. (2014) and Becker et al. (2014) did not include a pretest for mathematics performance, however, and therefore whether both skills would uniquely predict mathematics performance above and beyond prior performance is unclear. Furthermore, both Cameron et al. (2012) and Becker et al. (2014) focused on only one type of mathematics assessment (i.e., applied problem solving), leaving open the possibility that relations between EF and visuospatial skills and concurrent and later mathematics might be different for other types of mathematics (e.g., geometry). The present study examined both concurrent and longitudinal relations between EF, VMI, and multiple measures of mathematics performance in a sample of low-SES children, in order to explore whether EF and VMI predict improvement across a variety of types of mathematics performance in this population during early elementary school.

1.3.1. Potential for a compensatory effect of EF and visuospatial skills

There is a nuanced relationship between EF and visuospatial skills (Cameron et al., 2016) due in part to the fact that both draw from the same limited cognitive resource (Floyer-Lea & Matthews, 2004). This relationship appears to have implications for academic functioning: for example, in one low-SES sample of 4-year-olds, interaction effects between aspects of EF and VMI were found such that good VMI compensated for low inhibitory control in predicting gains in academic outcomes, including emergent literacy and behavior (Cameron et al., 2015). In other words, gains in these outcomes for children with low inhibitory control were similar to those with strong inhibitory control if they exhibited strong VMI ability. However, others have not replicated this result in elementary school for outcomes such as classroom behaviors (Kim et al., 2016). Thus, this study explores the potential that compensatory interaction effects between EF and VMI may also exist in the current, low-SES sample for a variety of mathematics performance measures, for which such interactions have not been investigated.

2. Present study

This study had two broad aims. The first aim was to determine, in a low-SES sample, the unique contribution of EF and VMI to children's concurrent early mathematics performance at the beginning of the school year (Time 1) and to improvement in their mathematics performance through the end of the school year (Time 2, controlling for Time 1). This study was largely expected to replicate previous findings; specifically, both EF and VMI were expected to significantly predict mathematics performance concurrently (at Time 1, as in Verdine, Golinkoff et al., 2014 and Cameron et al., 2012) and longitudinally (at Time 2, controlling for Time 1, as in Cameron et al., 2012 and Becker et al., 2014).

The second aim was to explore a potential compensatory association between EF and VS on concurrent mathematics performance and improvement in mathematics performance. In other words, we sought to investigate whether EF and visuospatial skills additively predicted mathematics, or whether strengths in only one skill sufficed for strong mathematics performance. Such compensatory effects have been found for literacy outcomes in a low-SES preschool sample (Cameron et al., 2015), though questions remain about whether this pattern will emerge for mathematics measured in elementary school.

3. Method

The present, observational and exploratory study, is based on data from an experimental study of an intervention targeting fine motor skills and delivered in the context of an afterschool, social and emotional learning program serving three urban elementary schools in a large city in the southeastern United States. Children were recruited from their schools before being randomized into either a treatment condition (offered opportunity to receive intervention) or a control condition (not offered opportunity to receive intervention). The intervention was administered over the course of one school year. Only the intervention delivered to treatment children in the first cohort was found to have effects; these were on attention and visuospatial skills, but not mathematics (Grissmer et al., 2013). The present study is observational and exploratory in nature, in that it has a correlational design − without strong causal warrant − and utilizes data which were ultimately collected for a different purpose. With respect to the second study aim in particular, we do not have firm hypotheses regarding whether compensatory effects may be more or less prominent for specific types of mathematics. Sensitivity analyses, described further below, were conducted to test whether the participation in the intervention may have interfered with our study results.

3.1. Participants

Participants were 162 children in kindergarten (n = 89) and first grade (n = 73) who were recruited in two successive cohorts of 97 and 65 children, respectively. Children were assessed at the start (Time 1) and end (Time 2) of the school year, before and after delivery of the aforementioned intervention. Average age at Time 1 was 5.5 years (SD_{months} = 4.0) for kindergarteners and 6.6 years (SD_{months} = 4.5) for first graders; average time between Time 1 and Time 2 assessments was 6.5 months. All children in the afterschool program were eligible to participate in the broader study, with the exception of those with severe disabilities that would prevent them from completing the assessment battery. Of the 162 children included in this study, 50% were boys, 92% were African American, and 95% qualified for free or reduced-price lunch, which roughly reflects the demographic characteristics of the student population served by the schools from which students were recruited.

3.2. Measures

EF and VMI were tested using the Developmental Neuropsychological Assessment (NEPSY; Korkman et al., 1998), a neuropsychological battery normed for ages 3–12 years. The NEPSY comprises subtests that measure five broad neuropsychological domains, including Attention/Executive Functions and Visuospatial Processing. Herein we provide internal and stability reliability information for these measures, when possible. For some, we include only stability reliability coefficients (i.e., test-retest coefficients between Time 1 and Time 2 assessments) because for these tests internal reliability is not appropriate due to dependency between item-level scores and/or multidimensionality in the scores (e.g., as in the use of both time and accuracy in the scoring criteria; Korkman et al., 1998).

3.2.1. Executive functioning

The NEPSY Attention/EF domain score comprised three subtests: Tower, Auditory Attention and Response Set, and Visual Attention. On Tower, children were shown pictures of three colored balls on three pegs and asked to copy the pattern in a set number of moves using a physical set of three balls and pegs. Correctly-executed sequences within a time limit were scored as correct. There were 20 items, and thus possible raw scores were 0–20. The test was discontinued if and when a child incorrectly responded to four consecutive items. Tasks similar to Tower (e.g., Tower of London, Tower of Hanoi) have elsewhere been described as broad or complex EF tasks, in that they require executive planning and problem solving, as opposed to only tapping a single component of EF, such as working memory or inhibitory control (Culbertson & Zillmer, 1998; Miyake et al., 2000). Internal reliability (Cronbach's alpha) for Tower was 0.84 at Time 1 and 0.88 for Time 2, and test-retest reliability was $r = 0.54$.

On Auditory Attention and Response Set, children heard recorded lists of color and non-color words in two trials. On trial 1, children were instructed to place a colored piece of foam in a box when they heard that color. The rules were changed for trial 2, such that responses depended on which color word was heard. Depending on the word, instructions dictated a word color and foam color match, mismatch, or no response. For example, the word "yellow" indicated that children should put a red piece of foam in the box, and the word "red" indicated that they should put a yellow piece of foam in the box. Correct responses were those that followed the rule in under 3 s (higher scores were given for quicker responses). This task required that children utilize their attention and working memory to act in accordance with the instructions and rules. Because rules changed between trial 1 and trial 2, this task also required inhibitory control and cognitive flexibility in order to inhibit performing according to previously used rules. The test-retest reliability of the Auditory Attention and Response Set subtest in this sample was $r = 0.49$.

On Visual Attention, children chose a target picture (trial 1) or pictures (trial 2) from an array of similar pictures presented on paper. Responses were scored as correct if children circled the target pictures in the array within a set time limit of 3 min. Performance on this task reflects a child's ability to focus selectively on and maintain attention to visual targets in the process of a visual search. The test-retest reliability of the Visual Attention subtest scaled scores in this sample was $r = 0.30$.

EF core domain scores, which are meant to represent a child's performance relative to a normed population and, were calculated according to NEPSY guidelines (Korkman et al., 1998), were used as the final measure of EF. Core domain scores take into account all subtests within each domain, consider child age, and are scaled so that, in the normative sample, the mean is 100 and standard deviation is 15 points. The core domain test-retest reliability scores for the Attention/Executive domain was $r = 0.60$.

3.2.2. Visuomotor integration

VMI was measured using the Design Copying subtest of the NEPSY Visuospatial Processing domain. On this test, children used paper and pencil to copy two-dimensional geometrical designs of increasing complexity. Designs were scored according to established criteria, with up to four points awarded on each of 18 items and, hence, a maximum score of 72. The test was discontinued if and when a child incorrectly responded to four consecutive items. Internal reliability (Cronbach's alpha) for Design Copying in this sample was 0.79 at Time 1 and 0.72 at Time 2; test-retest reliability was $r = 0.72$.

3.2.3. Mathematics performance

Mathematics performance was assessed using direct assessments from three different validated test batteries: the Woodcock-Johnson III (WJ III) Tests of Achievement (Woodcock, McGrew, Mather, & Schrank, 2001), KeyMath3-3 (Connolly, 2007), and the Test of Early Mathematics Ability-3 (TEMA; Ginsburg & Baroody, 2003). Composite mathematics scores were calculated at each time point by averaging the z-scores for each test.

3.2.3.1. Woodcock-Johnson applied problems. The WJ III Applied Problems subtest assesses the ability to analyze and solve math problems in context. Because the problems are presented within multiple modalities (pictures, word problems, etc.), children must ignore extraneous information, recognize which procedure to use, and then perform the appropriate calculations. For example, children were shown a picture of five cookies and were asked, "If Jessica ate three of these cookies, how many cookies are left?" The ability to solve later items requires specific knowledge, such as coin denominations and how to read a clock. In this sample, Cronbach's alpha was 0.79 and 0.80 at Time 1 and Time 2, respectively, with a test-retest reliability of $r = 0.63$.

3.2.3.2. KeyMath3 3. KeyMath3 (Connolly, 2007) is a norm-referenced measure designed to assess mathematics ability from ages 4 years, 6 months to 21 years. It is often used to identify gaps in students' knowledge and skills for the purpose of tailoring individualized interventions. It comprises three broad content areas aligned with the National Council of Teachers of Mathematics (NCTM)'s Principles and Standards for School Mathematics (2000). Three subtests from the Basic Concepts area were used: Numeration, Geometry, and Measurement. Within each subtest, administration was discontinued if and when a child incorrectly answered four consecutive items incorrectly. The Numeration subtest (up to 49 items possible) covers a wide range of foundational mathematical concepts and skills from basic number concepts through place value and eventually exponents and square roots. Children were administered at most 17 Numeration items in the fall, with internal reliability of those items at that time point being 0.75; they were administered at most 25 Numeration items in the spring, with an internal reliability of those items at that time point being 0.80. Test-retest reliability of the Numeration subtest was 0.67.

The Geometry subtest (up to 36 items possible) assesses students' ability to identify and analyze two- and three-dimensional shapes in addition to aspects of spatial relationships and reasoning. Children were administered at most 25 Geometry items in the fall, with internal reliability of those items at that time point being 0.75; they were administered at most 29 Geometry items in the spring, with an internal reliability of those items at that time point being 0.74. Test-retest reliability of the Geometry subtest was 0.54.

The Measurement subtest (up to 40 items possible) covers the ability to compare and measure objects in standard and non-standard units across a range of domains, including distance, size, volume, money, and time. Children were administered at most 12 Measurement items in the fall, with internal reliability of those items at that time point being 0.73; they were administered at most 21 Measurement items in the spring, with an internal reliability of those items at that time point being 0.81.

Table 1
Sample Characteristics and Descriptives

	Kindergarteners					First Graders				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Age T1 (months)	88	66.55	3.96	60	75	70	79.03	4.53	69	92
Age T2 (months)	84	73.2	3.96	67	83	68	85.42	4.48	79	99
Gender (1 = Male)	89	0.52	0.50	0	1	73	0.48	0.50	0	1
Race (1 = Black)	89	0.94	0.23	0	1	73	0.90	0.30	0	1
FRL (1 = eligible)	83	0.96	0.19	0	1	71	0.93	0.26	0	1
Offered Treatment (1 = Offered Treatment)	89	0.51	0.50	0	1	73	0.58	0.50	0	1
EF Core Domain Score T1	75	81.35	13.2	53	121	67	85.57	15.1	54	121
EF Core Domain Percentile T1	75	17.27	18.8	0.1	92	67	25.02	25.6	0.1	92
Design Copy (VMI) Score − T1	87	−3.49	7.66	−30	12	70	−0.05	1.15	−2.3	2.6
WJ − Applied Problems Raw Score − T1	89	12.66	3.58	2	20	73	17.91	3.95	7	25
WJ − Applied Problems Raw Score − T2	84	17.46	3.73	5	26	68	23.06	4.03	12	32
TEMA Raw Score − T1	89	14.70	8.10	0	32	72	28.99	9.12	4	57
TEMA Raw Score − T2	83	27.65	8.81	3	40	68	38.52	7.18	16	59
KeyMath3 Raw Composite Score − T1	89	11.17	5.01	2	21	73	17.48	6.21	4	32
KeyMath3 Raw Composite Score − T2	84	17.00	5.51	2	30	68	27.49	7.74	12	54
KeyMath3 Raw Geometry Score − T1	89	6.04	3.06	0	13	73	7.90	3.01	0	16
KeyMath3 Raw Geometry Score − T2	84	8.23	2.95	0	15	68	11.01	3.03	5	18
KeyMath3 Raw Measurement Score − T1	89	1.28	1.31	0	4	73	3.26	2.15	0	8
KeyMath3 Raw Measurement Score − T2	84	2.88	1.81	0	7	68	6.21	3.32	0	16
KeyMath3 Raw Numeracy Score − T1	89	3.84	1.81	0	8	73	6.11	2.47	2	14
KeyMath3 Raw Numeracy Score − T2	84	5.89	2.04	2	12	68	10.03	2.81	4	21

Notes: T1 = Time 1; T2 = Time 2; FRL = receiving free/reduced price lunch; EF = executive function; VMI = visuomotor integration. Means for binary variables to be interpreted as percentages (e.g., gender composition of kindergarteners is 52% male, racial composition of first graders is 90% Black).

Test-retest reliability of the Measurement subtest was 0.67.

Raw scores from these three subtests were summed to create aKeyMath3 Composite score, which in this sample had an internal reliability of 0.87 and 0.90 in the fall and spring, respectively, and a test-retest reliability of $r = 0.79$.

3.2.3.3. Test of early mathematics ability. Unlike Woodcock-Johnson Applied Problems and KeyMath3, which were designed to test math into adulthood, the TEMA (Ginsburg & Baroody, 2003) is a 72-item assessment specifically designed for young children from three to eight years old. It also includes items that assess both informal math concepts and skills (those learned in the home or neighborhood) and formal math concepts and skills (those learned in school). Informal concepts and skills include, among others, small number perception, modeling addition and subtraction using objects, understanding part-whole relations, verbal counting, understanding cardinality, and constructing a mental number line. Formal concepts and skills include reading and writing numerals, addition and subtraction facts, and written addition and subtraction procedures. Starting point for administration of TEMA items was adjusted based on a child's age and assessment administration was discontinued if a child answered 8 consecutive items incorrectly. In this sample, at least one child was assumed to have answered all 72 items at each time point, and the internal reliability was 0.97 and 0.65 at Time 1 and Time 2, respectively, and test-retest reliability was $r = 0.79$.

3.4. Analytic plan

Analyses were conducted in Mplus v. 7.0 (Muthén & Muthén Muthén, 1998–2010) and using maximum likelihood estimation, robust standard errors to account for children being nested within classrooms throughout the school year, and multiple imputation in order to address missing data.

3.4.1. Multiple regressions

Multiple regression models were used to examine associations between cognitive skill predictors and mathematics performance at Time 1 (Models 1A through 1U) and at Time 2, controlling for Time1 (Models 2A through 2U). Analyses were conducted using composite mathematics (average of z-scores across the three mathematics measures) and, as follow-up analyses, each measure of mathematics performance − including models for each of the KeyMath3 subtests. For each time point, a model with covariates only (e.g., as in Models 1A and 2A) was tested prior to simultaneous entry of EF and VMI (e.g., as in Models 1B and 2B) to understand how much variance these skills explained above and beyond covariates. All models included gender (0 = female; 1 = male), grade (0 = kindergarten; 1 = first grade), and treatment condition (0 = not offered treatment; 1 = offered treatment) as covariates. Age was not included as a covariate because it was not a significant predictor of mathematics performance after controlling for grade. Further, the models predicting Time 2 mathematics performance included Time 1 mathematics performance as a predictor. To test potential interaction effects between EF and VMI, interaction terms were added to the models (e.g., Models 1C and 2C). EF and VMI were centered prior to creating the interaction variable in order to ease interpretation of results.

For each regression, a Wald test was run in order to determine whether adding EF and VMI (or their interaction) as predictors increased the amount of explained variance in the mathematics performance outcomes. Then, the regression coefficients were examined to understand whether and to what extent each skill (or interaction) predicted mathematics performance above and beyond other predictors, as indicated by the statistical significance and magnitude of each coefficient, respectively.

3.4.2. Missing data

Table 1 makes evident that missing data was a minor issue in this study. Most variables ranged from 0 to 14 missing observations in the amount of missing data. NEPSY Attention/EF domain scores could not be calculated for 13 children due to experimenter error, but other missing data was due to study attrition. As mentioned above, analyses used MI, conducted in Mplus. MI in Mplus uses Markov Chain Monte Carlo simulations, using 100 iterations to generate each imputed data set (see Asparouhov & Muthén, 2010). We imputed 10 data sets, on which analyses were conducted and pooled.

3.4.3. Observational studies with experimental data: sensitivity analyses

Because these analyses were based on data collected as part of an intervention study, it is reasonable to be concerned about whether the intervention may affect relations among constructs. In this particular study, the treatment group's condition was designed to improve fine motor skills, but was also found to improve EF and visuospatial skills for the first of the two cohorts represented in the current study sample (Grissmer et al., 2013). Thus, sensitivity analyses were conducted to understand whether and to what extent results were affected by the intervention. Specifically, the same analyses as described above were conducted, but with models including interaction term(s) between variables of interest (EF, VMI, and their interaction) and a dummy variable coded as 1 for children from the first cohort who were assigned to treatment and as 0 for all other children. These terms were included in imputation models as well as analytic models. We conducted Wald tests in order to understand whether adding these interaction terms increased the amount of variance explained in the outcome in question. We also examined the statistical significance of the coefficients for these terms in analytic models, which would indicate whether associations between constructs was different for the first cohort's treatment group, as compared to all other children.

4. Results

Children in this sample performed low on EF skills relative to the normative NEPSY sample (See Table 1): average percentile ranks for the Attention/EF domain were in the 17th percentile for kindergarteners and 25th percentile for first graders. These descriptive statistics demonstrate the extent to which the current, low-SES sample would be considered less advantaged than those of other studies discussed above (e.g., Blair & Razza, 2007; Cameron et al., 2012).

Bivariate correlations (see Table 2) were computed among all EF and VMI assessments and mathematics outcomes at both time points. In general, all correlations were in the expected direction. For instance, EF domain scores and VMI scores were positively correlated ($r = 0.33$, $p < 0.001$), as were EF and VMI with each mathematics assessment.

4.1. Contributions of time 1 EF and VMI to mathematics performance

Regression model estimates for both concurrent and longitudinal analyses for composite mathematics scores are shown in Table 3. Regression model estimates for individual mathematics measure scores for concurrent and longitudinal analyses can be found in Supplemental Tables S4 and S5, respectively.

Adding EF and VMI to the concurrent models (e.g., comparing Model 1A and 1B) significantly increased the amount of variance explained, above that explained by covariates, in Time 1 composite mathematics performance by 16% (Wald statistic = 28.52, $\Delta df = 2$, $p < 0.001$; see Table 3). The increase in amount of variance explained was also significant for all three mathematics assessments, as well as each KeyMath3 subtest: by at least 10% (for KeyMath3 Geometry; Wald statistic = 14.9, $\Delta df = 2$, $p < 0.001$) and at most 16% (for the KeyMath3 Composite, Wald statistic = 29.95, $\Delta df = 2$, $p < 0.001$; see Table S4). Both skills had significant associations with Time 1 composite mathematics performance as well as across all individual measures.

Table 3
Concurrent and Longitudinal Regression Models for Composite Mathematics.

Estimate(SE)	Concurrent Models – Composite Mathematics T1			Longitudinal Models – Composite Mathematics T2		
	Model 1A	Model 1B	Model 1C	Model 2A	Model 2B	Model 2C
First Grade	1.22*** (0.11)	0.87*** (0.14)	0.87*** (0.14)	0.30** (0.09)	0.27** (0.10)	0.27** (0.10)
Male	−0.29 (0.14)	−0.17 (0.13)	−0.17 (0.13)	0.05 (0.06)	0.07 (0.07)	0.08 (0.07)
Received Treatment	−0.04 (0.10)	0.05 (0.09)	0.05 (0.09)	−0.03 (0.09)	0.01 (0.08)	0.01 (0.08)
Composite Mathematics T1				0.86*** (0.06)	0.74*** (0.06)	0.74*** (0.06)
EF T1		0.28*** (0.06)	0.28*** (0.06)		0.11** (0.04)	0.11** (0.04)
VMI T1		0.26*** (0.07)	0.26*** (0.07)		0.15** (0.05)	0.14** (0.05)
EF X VMI T1			0.00 (0.06)			−0.03 (0.05)
R^2	0.39***	0.55***	0.55***	0.79***	0.82***	0.82***
Wald Statistic		28.52***	0.00		16.82***	0.54

*$p < .05$, **$p < .01$, ***$p < .001$.
NOTES: EF = Executive Function Core Domain Score; VMI = Visuomotor Integration (Design Copy); T1 = Time 1; T2 = Time 2. The Wald statistic shown for each model tests whether parameters existing in the respective model, but not in the model presented immediately to its right, add significant variance explained in the predictor.

Table 2
Correlations Among Study Variables

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.
1.	First Grade	**1**																		
2.	Male	−0.04	**1**																	
3.	Offered Treatment	0.07	0.09	**1**																
4.	EF T1	0.15	−0.09	−0.14	**1**															
5.	Design Copy T1	**0.47**	**−0.18**	−0.02	**0.33**	**1**														
6.	WJ App. Probs. T1	**0.56**	**−0.17**	0.00	**0.42**	**0.50**	**1.00**													
7.	WJ App. Probs. T2	**0.58**	−0.04	0.07	**0.43**	**0.56**	**0.78**	**1.00**												
8.	TEMA T1	**0.65**	−0.14	0.01	**0.40**	**0.53**	**0.77**	**0.71**	**1.00**											
9.	TEMA T2	**0.56**	−0.11	0.02	**0.45**	**0.57**	**0.74**	**0.77**	**0.78**	**1.00**										
10.	KM3 Composite T1	**0.48**	**−0.16**	0.02	**0.41**	**0.53**	**0.78**	**0.67**	**0.76**	**0.72**	**1.00**									
11.	KM3 Composite T2	**0.47**	−0.05	−0.01	**0.46**	**0.61**	**0.78**	**0.83**	**0.81**	**0.80**	**0.80**	**1.00**								
12.	KM3 Geometry T1	**0.29**	**−0.18**	0.06	**0.27**	**0.40**	**0.61**	**0.50**	**0.56**	**0.55**	**0.85**	**0.60**	**1.00**							
13.	KM3 Geometry T2	**0.50**	−0.16	−0.02	**0.33**	**0.53**	**0.65**	**0.67**	**0.61**	**0.65**	**0.67**	**0.85**	**0.56**	**1.00**						
14.	KM3 Measurement T1	**0.65**	−0.08	−0.02	**0.44**	**0.47**	**0.68**	**0.62**	**0.66**	**0.62**	**0.79**	**0.71**	**0.45**	**0.54**	**1.00**					
15.	KM3 Measurement T2	**0.61**	−0.09	0.09	**0.47**	**0.51**	**0.70**	**0.73**	**0.73**	**0.69**	**0.70**	**0.89**	**0.49**	**0.61**	**0.67**	**1.00**				
16.	KM3 Numeracy T1	**0.42**	−0.04	−0.03	**0.35**	**0.48**	**0.68**	**0.60**	**0.72**	**0.66**	**0.85**	**0.71**	**0.53**	**0.57**	**0.64**	**0.64**	**1.00**			
17.	KM3 Numeracy T2	**0.54**	−0.09	−0.11	**0.41**	**0.55**	**0.70**	**0.77**	**0.78**	**0.76**	**0.72**	**0.89**	**0.52**	**0.60**	**0.65**	**0.74**	**0.67**	**1.00**		
18.	Composite Math T1	**0.61**	**−0.17**	0.01	**0.45**	**0.57**	**0.92**	**0.79**	**0.92**	**0.81**	**0.92**	**0.86**	**0.73**	**0.70**	**0.77**	**0.77**	**0.81**	**0.80**	**1.00**	
19.	Composite Math T2	**0.63**	−0.12	0.01	**0.48**	**0.62**	**0.82**	**0.93**	**0.82**	**0.92**	**0.79**	**0.94**	**0.59**	**0.78**	**0.70**	**0.83**	**0.71**	**0.87**	**0.88**	**1.00**

Notes: Correlations were calculated using listwise deletion.
First Grade coded as 0 = Kindergarten, 1 = First Grade; Male coded as 0 = Female, 1 = Male; Offered Treatment coded as 0 = not offered treatment, 1 = offered treatment; EF = Executive Function Cored Domain Score; T1 = Time 1; WJ App. Probs. = Woodcock Johnson Applied Problems; TEMA = Test of Early Mathematics Ability; KM3 = KeyMath3. Bold indicates significant correlation with 95% confidence level ($p < 0.05$).

The magnitude of the association between EF and composite mathematics was $\beta = 0.28$ ($p < 0.001$). For each individual mathematics measure, the coefficient for EF was at least $\beta = 0.16$ (KeyMath3 Geometry, $p < 0.05$) and up to $\beta = 0.31$ (KeyMath3 Composite and KeyMath3 Measurement, $p < 0.001$). The magnitude of the association between VMI and composite mathematics was $\beta = 0.26$ ($p < 0.001$). For each individual mathematics measure, the coefficient for VMI was at least $\beta = 0.20$ (KeyMath3 Measurement, $p < 0.01$) and up to $\beta = 0.27$ (KeyMath3 Geometry and KeyMath3 Numeracy, $p < 0.001$).

Adding EF and VMI to the models predicting Time 2 (e.g., comparing Model 2A and 2B) performance significantly increased the amount of variance explained in composite mathematics by 3% (Wald Statistic = 16.82, $\Delta df = 2$, $p < 0.001$; see Table 3). The increase in amount of variance explained was also significant for all three mathematics assessments, as well as each KeyMath3 subtest: by at least 3% (KeyMath3 Composite, Wald Statistic = 69.77, $\Delta df = 2$, $p < 0.001$) and up to 7% (KeyMath3 Geometry, Wald Statistic = 85.95, $\Delta df = 2$, $p < 0.001$; see Table S5). Further, both skills significantly predicted improvement in composite mathematics performance and across almost all individual mathematics measures. The partial effect of EF was significant for composite mathematics ($\beta = 0.11, p < 0.01$), as well as for five out of six individual measures, and was as large as $\beta = 0.20$ (KeyMath3 Measurement, $p < 0.01$). The exception to this statement was KeyMath3 Geometry ($\beta = 0.10$, $p = 0.11$). The partial effect of VMI was significant for composite mathematics ($\beta = 0.15, p < 0.01$), as well as for all six measures, ranging from $\beta = 0.13$ (KeyMath3 Measurement, $p < 0.05$) to $\beta = 0.26$ (KeyMath3 Geometry, $p < 0.001$).

4.2. Potential interaction effects between EF and VMI

To test the compensatory pattern of cognitive skills on mathematics performance, we added an interaction term between EF and VMI to the models described immediately above (e.g., Models 1C and 2C). The interaction term did not explain significant variance above and beyond covariates and EF and VMI for composite mathematics performance either concurrently (Wald statistic = 0.00, $\Delta df = 2$, $p = 0.96$) or longitudinally (Wald statistic = 0.54, $\Delta df = 2$, $p = 0.46$; see Table 3). The change in explained variance was statistically significantly different from zero for only two individual outcomes: concurrent KeyMath3 Geometry (Table S4, Model 1O: Wald statistic = 5.08, $\Delta df = 1$, $p < 0.05$; $\beta = -0.17, p < 0.05$) and Time 2 TEMA (Table S5, Model 2I: Wald statistic = 2.06, $\Delta df = 1$, $p < 0.05$; $\beta = -0.16$, $p < 0.05$). The nature of the interaction for both of these outcomes was compensatory, as hypothesized: children with *either* high VMI *or* high EF performed better on Time 1 KeyMath3 Geometry and Time 2 TEMA than children who were weak in both skills (Figs. 1 and 2 illustrating these relations are available as part of online, supplementary materials). We note that while the nature of this interaction for these outcomes was as hypothesized, we did not hypothesize that this interaction would exist for only two of 16 tests for said interaction.

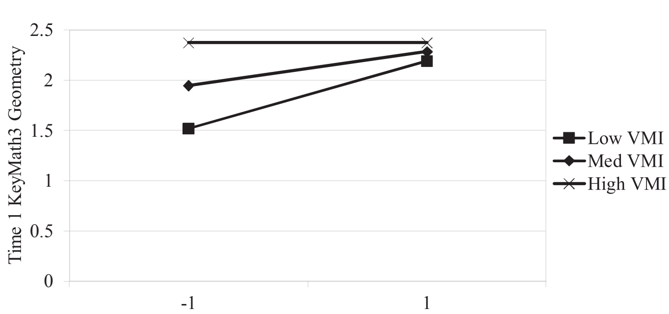

Fig. 1. Compensatory Effect between EF and VMI for Time 1 KeyMath3 Geometry.

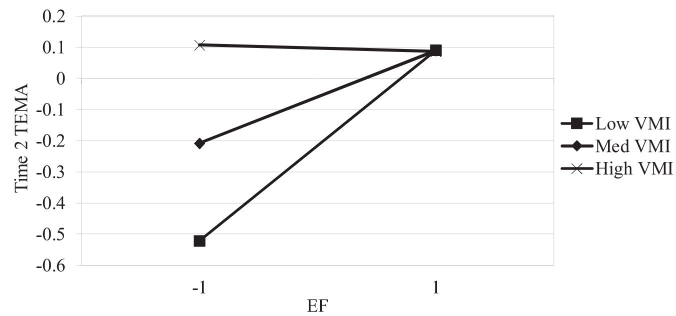

Fig. 2. Compensatory Effect between EF and VMI for Time 2 TEMA.

4.3. Covariate effects

In the concurrent models, grade was the only covariate related to mathematics outcomes after controlling for EF and VMI: not surprisingly, first graders outperformed kindergarteners in composite mathematics and across all individual measures. There was a gender effect in two of the covariates-only concurrent models, with girls outperforming boys on WJ Applied Problems and KeyMath3 Geometry, but this advantage did not persist after inclusion of EF and VMI. Across longitudinal models, grade was, again, the only covariate related to outcomes after controlling for EF and VMI: first graders outperformed kindergartners across all measures, even after controlling for Time 1 performance. In other words, the longitudinal models suggest first graders showed more improvement in mathematics performance, on average, than kindergarteners over the course of the school year.

4.4. Sensitivity analyses: testing for interference of intervention in producing results

In order to ensure that intervention effects from the larger study did not interfere with relations observed among constructs at Time 2 (the post-intervention time point), we ran analyses identical to those described above, but including an interaction term between variables of interest (i.e., EF, VMI, and their interaction) and a dummy variable indicating whether each child was in the treatment group in the study cohort which had significant treatment effects. In no model did this interaction term add significant variance to the outcome. For Time 2 TEMA, despite an insignificant Wald statistic, the treatment X EF coefficient was significant ($\beta = -0.12$, $p < 0.05$), but this indicates that the association between EF and Time 2 TEMA was weaker for the group of children offered treatment. Therefore, if being offered an opportunity to participate in the intervention affected our results with respect to this outcome, it did so by decreasing the magnitude of the partial EF effect. Thus, we conclude that any intervention effects are not responsible for the patterns of associations we have found and as described above; if anything, intervention effects may have attenuated observed associations.

5. Discussion

This study examined the extent to which two cognitive skills, EF and VMI, measured at the beginning of the school year (Time 1), were associated with concurrent mathematics performance and longitudinally with improvement in mathematics performance through the end of the school year (Time 2) in a low-SES sample of kindergarteners and first graders. Results suggest that both skills are associated with concurrent performance as well as improvement in performance on overall mathematics performance, as well as on most individual mathematics assessments included in this study. Results do not support a compensatory pattern, or any other type of interaction effect, for these cognitive skills in relating to overall mathematics performance, nor to most (12 out of 14) individual measures of mathematics performance, in early elementary school, except for concurrent KeyMath3 geometry performance and improvement in TEMA performance.

This study replicated previously established links between EF and early academic skills before, during, and after the transition to formal schooling (e.g. Blair & Razza, 2007; Duncan et al., 2007; McClelland et al., 2007). In particular, these results are closely aligned with those reported by Blair and Razza (2007) which found, in a low-income sample, that preschoolers with higher EF had stronger early math and reading skills at the end of kindergarten. The current study finds much the same, with the added strength of analyses controlling for Time 1 mathematics performance; in other words, we found that children who began the school year with higher EF made larger improvements in mathematics performance than those who entered with lower EF. This was the case for overall mathematics, as well as for five out of six mathematics outcomes, the exception being KeyMath3 Geometry.

Previous work has underscored the importance of EF for successfully meeting the new challenges of formal schooling, such as more complex academic tasks that require strategy selection and manipulation of mental models (Bull & Scerif, 2001; Fuchs et al., 2010b) and navigating the classroom environment (Rimm-Kaufman, Pianta, & Cox, 2000). Children with low EF are likely to have difficulty with both, which would explain why EF predicts Time 2 mathematics performance on most assessments even after taking Time 1 mathematics performance into account.

This study extended past research by suggesting that VMI relates to both concurrent mathematics performance as well as improvement in mathematics performance, even after controlling for EF. Evidence for a link between visuospatial skills and mathematics ability spans brain imaging (e.g. Hubbard, Piazza, Pinel, & Dehaene, 2005), disabilities (e.g. O'Hearn & Landau, 2007), and adult numerical cognition research (e.g. Dehaene, Bossini, & Giraux, 1993). To date, however, relatively fewer studies have addressed visuospatial skills and mathematics performance in young children, especially when controlling for other potential confounds, such as EF. This study establishes that even if children have strong executive skills, VMI appears to have an additional, unique association with improvement in most measures of mathematics performance. This could be due to the heavy incorporation of manipulatives and other visual and tactile aids in early elementary mathematics instruction (Guarino, Dieterle, Bargagliotti, & Mason, 2013). Even if children can pay attention and control impulses, they also need to be able to visualize and work with materials. Alternatively, the pattern of findings could be due to co-development in visuospatial and mathematics skills, which rely on similar neural networks (Hubbard et al., 2005).

That both EF and VMI were related to concurrent KeyMath3 Geometry, but only VMI predicted improvement in KeyMath3 Geometry, could reflect this particular assessment's emphasis on spatial reasoning. For example, in this assessment students are asked to describe the location of a person in a picture, match pictures of a kitten in different positions, identify left and right, and identify what a picture would look like if rotated. These tasks are less formal than items in most of the other assessments in this study, and therefore the lack of longitudinal EF effect may reflect that these skills are less explicitly taught in instruction throughout the year.

In slight contrast to other studies suggesting a compensatory effect between EF and VMI for supporting emergent literacy and classroom behavior among 3- to 5-year-olds (Cameron et al., 2015), this study found no interaction effect between EF and VMI on overall mathematics and on most aspects of mathematics performance, except for on concurrent geometry performance and on improvement on TEMA. This discrepancy between this study and Cameron et al. (2015) could be due to age differences where cognitive skills are more likely to compensate for each other in younger children. Consistent with that line of reasoning, Cameron et al. (2012) tested but did not find that EF and VMI interacted in relation to kindergarten academic achievement, including in mathematics problem solving. This study largely suggests the same, but demonstrates that such an interaction may exist for other types of mathematics performance (i.e., concurrent Geometry and improvement in informal mathematics, as measured by TEMA).

The nature of the interaction between EF and visuospatial skills for beginning-of-year (concurrent) geometry performance and end-of-year (later) TEMA performance was such that children performed almost equally well if they had high EF, high VMI, or both, but not if they scored low on both. As mentioned previously, the KeyMath3 Geometry subtest included many informal items; likewise, a majority of items answered correctly by children on the TEMA at both the beginning and end of the year measured informal math skills. Thus, this interaction may suggest that strong visuospatial skills may compensate for low EF in using or developing informal mathematics skills. For example, a child who has difficulty planning out or following the steps of a simple addition problem may nevertheless arrive at the correct answer if he or she can manipulate and arrange objects in space to model the problem. The presence of an interaction at the end, but not the beginning, of the year for TEMA could suggest that children with low EF may rely on their relatively stronger VMI to benefit from classroom instruction, to the extent such instruction is provided.

5.1. Strengths and limitations

This study was one of the first to utilize normed neuropsychological assessments of both EF and visuospatial skills to examine their contributions to early mathematics performance. While the small sample size allowed for thorough testing, it also limited the generalizability of the results. These low-SES children from one school district are not likely to be representative of low-SES early elementary-aged children in all regions of the country.

Another limitation is the observational nature of the study. While controlling for prior mathematics performance in our longitudinal analyses lends some support for the notion that EF and visuospatial skills might contribute to mathematics learning, our analyses do not demonstrate causal relationships. On a related note, we have not controlled for several potential confounds in our analyses, such as language and intelligence; whether our results would hold after doing so cannot be known.

Measurement of mathematics performance here was more thorough than in previous studies using only one measure, in that three psychometrically validated measures of mathematics were used. This minimizes the possibility that the present findings of unique associations between EF and mathematics and VMI and mathematics are unique to a certain type of mathematics measure or set of skills, as they were consistent across most measures. On the other hand, we acknowledge that running models across this many mathematics assessments effectively resulted in 16 separate tests seeking an EF X VMI interaction, and therefore, we may have found significant interactions for Time 1 Geometry and Time 2 TEMA by chance.

Measurement of cognitive skills, on the other hand, may be a concern despite the use of validated assessments. First, reliabilities for several EF subtests were somewhat low, and may reflect the fact that the NEPSY assessment was normed/standardized on a nationally representative sample of children, whereas the sample included here is comprised largely of children from low-SES families. This low reliability suggests larger than desired measurement error and, ultimately, reduced power for detecting effects. Thus, imprecision in EF measurement could be to blame for why EF did not significantly predict improvement in KeyMath3 Geometry scores, despite having a positive regression coefficient. This underscores the need for psychometric work in low-SES populations, who are traditionally under-represented in psychological research. Second, the assessments used for EF simultaneously tapped multiple components of EF, disallowing independent tests of associations between various aspects of EF and mathematics. Given that different components of EF have been differentially related to academic outcomes in similarly-aged populations (Bull, Epsy, & Wiebe, 2008), future research should consider whether such differential relations hold even in the context of controlling for VMI.

Finally, given that the data utilized in this study were ultimately collected for a purpose other than examining the relation between EF, VMI, and mathematics performance (i.e., were collected as part of an evaluation study), the analyses should be regarded as exploratory. Future replication studies should be conducted in order to confirm whether the pattern of results holds.

5.2. Implications and conclusion

These analyses may inform thinking about the connection between cognitive development and academic achievement, including how the former might support the latter. This consideration may be especially important for children who come from low-SES households with fewer opportunities and greater challenges in their development of certain cognitive skills not typically explicitly taught or trained in school. In this study, EF and VMI were robust and unique predictors of improvement in mathematics performance in a sample of low-SES kindergartners and first graders. These findings are consistent with previous research and with the argument for the inclusion of these cognitive skills in the focus of early education policies and curricula (Blair, 2002, 2003; Rimm-Kaufman & Pianta, 2000; Ursache et al., 2012; Uttal & Cohen, 2012).

Importantly, both EF and VMI are sensitive to intervention and experience (Diamond, Barnett, Thomas, & Munro, 2007; Newcombe et al., 2013; Tang & Posner, 2009; Uttal et al., 2013). Promising intervention approaches targeting EF include novel, cohesive curricula implementable in preschool and kindergarten classrooms (Bierman & Torres, 2016; Diamond, 2012). There have been comparatively fewer implementations of curricula explicitly fostering visuospatial abilities, such as VMI, in early childhood, which has been called "the orphan of the academic curriculum" Newcombe et al., 2013, p. 44). Some researchers have begun efforts to flesh out the "When, Why, and How" of incorporating visuospatial development in early education efforts, proposing that explicit training of visuospatial skills has the potential to improve learning in mathematics and other science disciplines (e.g., Uttal & Cohen, 2012). For example, simple activities such as the use of spatial language, maps or models, and sensorimotor materials appear to support visuospatial development in young children and may be easily implementable within current early childhood curricula (see Newcombe et al., 2013). Thus, future research should investigate the extent to which the associations found here represent causal relationships and, relatedly, whether fostering these abilities transfers to improved mathematics learning later on.

The results of this study lend tentative support to those who advocate for a more diverse curriculum, with a broader focus on child development and incorporation of activities not explicitly tied to academic outcomes (e.g. Elkind, 2012; Stipek, 2006). Specifically, EF and visuospatial skills may be two cognitive skills that are theoretically important for children's early success in mathematics in elementary school. Given the demographics of our sample, our results suggest this is the case for children of color from low-income families in addition to previously studied, more socio-demographically advantaged families. Further research is required to evaluate the promotion of these skills as a means to improve academic outcomes for children, and such efforts are already underway (e.g., Grissmer et al., 2013). Results of such efforts should provide insights for how best to holistically support academic success for all children.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecresq.2017.08.005.

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