MIND, BRAIN, AND EDUCATION

# Longitudinal Associations Among Executive Function, Visuomotor Integration, and Achievement in a High-Risk Sample

**Laura L. Brock[1], Helyn Kim[2], and David W. Grissmer[3]**

**ABSTRACT**— The present study examines cross-lagged associations among executive function, visuomotor skills, and math and reading achievement from kindergarten to second grade. Both executive function and visuomotor integration tend to be delayed in socioeconomically disadvantaged children and can explain nearly half the achievement gap at kindergarten entry. Participants were 259 students enrolled in elementary schools serving predominantly low-income communities with multiple sociodemographic risk factors. Executive function at multiple time points predicted reading and math achievement. However, visuomotor integration in kindergarten alone predicted later reading and math. Initially, math predicts later reading. Subsequently, reading predicts later math.

Beyond basic academic skills, a number of foundational skills that support learning and achievement have been identified (Diamond, 2010). One of the most studied of these foundational skills is executive function (EF). Considered a complex skill set that underlies learning and behavioral regulation, EF includes sustaining attention, flexibility in shifting attention, inhibition of distracting impulses, and the capacity for maintaining, manipulating, and accessing information in working memory (Best & Miller, 2010; Diamond & Lee, 2011). Emerging research suggests visuomotor integration (VMI) is another domain-general foundational skill and describes the capacity to visually perceive and understand spatial relationships among objects (Carlson, Rowe, & Curby, 2013). VMI skills are evidenced when children coordinate fine motor movements to replicate designs or symbols. For example, in the classroom children employ VMI when they interpret, mentally represent, and copy visual information, including working with letters and numbers (Marr, Cermak, Cohn, & Henderson, 2003).

In preschool and at kindergarten entry, EF and VMI both contribute shared and unique variance to early reading and math achievement (Becker, Miao, Duncan, & McClelland, 2014; Cameron et al., 2012; Verdine, Irwin, Golinkoff, & Hirsh-Pasek, 2014). VMI compensated for low EF and vice versa in a study examining preschool literacy gains (Cameron et al., 2015). Examined separately, EF (Best, Miller, & Naglieri, 2011) and fine motor skills (operationalized as both VMI and motor coordination tasks; Grissmer, Grimm, Aiyer, Murrah, & Steele, 2010) contribute to achievement across childhood. In a diverse sample, both VMI and EF directly contributed to math achievement and vice versa, revealing bidirectional influences between math, EF, and VMI; by contrast fine motor coordination was only indirectly associated with math through its contribution to VMI (Kim, Duran, Cameron, & Grissmer, 2017).

Reading and math achievement also interrelate and support later performance. Before children are expected to read fluently, early math predicts later reading (Lerkkanen, Rasku-Puttonen, Aunola, & Nurmi, 2005), perhaps because

[1]College of Charleston
[2]Brookings Institute
[3]University of Virginia

Address correspondence to Laura L. Brock, Department of Teacher Education, College of Charleston, 66 George Street, Charleston, SC 29424; e-mail: brockll@cofc.edu

  

emergent readers and mathematicians direct a great deal of effort toward decoding symbols (letters and numbers). As expectations increase for children to read independently, reading skills are increasingly employed within math content (e.g., written instructions, word problems). By second grade, reading skills become an important predictor of math achievement (Hecht, Torgesen, Wagner, & Rashotte, 2001). The relation between reading and math is thought to be undergirded by common foundational cognitive processes, perhaps including EF and VMI (Cameron, Cottone, Murrah, & Grissmer, 2016).

Children living in poverty enter formal schooling with gaps in foundational skills that impede school readiness and achievement trajectories. Indeed, analyses of the Early Childhood Longitudinal Survey which followed approximately 20,000 children found that fine motor skills (which included both VMI and fine motor coordination tasks) explained nearly 40% of the achievement gap at kindergarten entry for African American boys living in poverty (Grissmer & Eiseman, 2008). Chronic exposure to stress, less opportunity for cognitive stimulation, and poor nutrition associated with endemic poverty impairs frontal lobe development (corresponding with EF pathways) and consequently dampens achievement trajectories (Hair, Hanson, Wolfe, & Pollak, 2015; Raver, Blair, & Willoughby, 2013). The present study explores cross-lagged associations between EF, VMI, and reading and math achievement from kindergarten entry to second grade in a sample of children with multiple sociodemographic risk factors. Less is known about how EF, VMI, reading, and math interrelate over time in high-poverty samples.

## METHOD

### Participants

Participants were 259 children (see Table 1; 119 boys and 137 girls) who were 4.8–6.4 years in age ($M = 5.41$ years; $SD = 0.33$) when they participated in direct assessment just prior to or at the beginning of the kindergarten year. Children attended one of four urban Title 1 elementary schools serving predominately low-income communities. Families that provided demographic information reported 96% of students were eligible for free or reduced-price lunch ($n = 226$). Overall, families who self-reported ethnicity identified as African American/Black (88%; $n = 213$), Hispanic/Latino (8%; $n = 19$), or Caucasian/White/other (4%; $n = 11$). Self-reported maternal education ranged from eighth grade or less to a master's degree, with 62 (26%) reporting less than a high school diploma. The current study used data from a larger randomized control trial that evaluated the effectiveness of a local after-school program. For the purposes of the present study, treatment condition was entered as a control variable and did not contribute significant variance to outcomes due to low participation in the program.

### Procedure

Families completed a demographic questionnaire when consent was obtained. Direct assessments were conducted on three occasions at kindergarten entry, first grade entry, and second grade entry. Testing occurred either during a school-sponsored summer program or during the school day at the beginning of the school year. The direct assessment batteries included the Head–Toes–Knees–Shoulders Task (HTKS), the Woodcock–Johnson Letter–Word Identification (LWID), the Woodcock–Johnson Applied Problems (AP), and the Beery–Buktenica Developmental Test of VMI.

### Measures

*Executive Function*

The HTKS is a 30-item direct assessment which requires a child to perform a motor function that is the opposite of a verbal instruction (Ponitz et al., 2008). For instance, when the student is told to touch his head, he must touch his toes, and vice versa; when told to touch his shoulders, he must touch his knees, and vice versa. The task increases in complexity across sections, introducing a rule switch (e.g., when ask to touch toes, the correct response is to touch knees). The measure taps multiple EFs including working memory (holding multiple rules in mind), inhibitory control, and attentional flexibility (switching rules). For each command, scores range 0 to 2: incorrect responses receive 0, self-corrected responses receive 1 point, and correct responses receive 2 points. Overall ability is assessed by the sum of points received.

*Visual-Motor Skills*

The Beery–Buktenica Developmental Test of VMI—sixth edition (Beery, Buktenica, & Beery, 2010) is a 30-item measure that requires children to copy increasingly complex designs by visually perceiving a geometrical design, mentally representing the design, and then employing fine motor skills to replicate the design. Scoring criteria are unique to each design depending upon skill assessed (e.g., degree of angle, extent of shape overlap, crossing the midline, etc.). Reliability and validity were established drawing from a representative sample of 1,737 individuals ages 2–18 years (Beery et al., 2010).

*Academic Achievement*

The Woodcock–Johnson Tests of Achievement III—Form B (Woodcock, McGrew, & Mather, 2001). LWID subtest

**Table 1**
Descriptive Statistics ($N = 259$)

| | n | % | % Missing | M | SD | Min | Max. |
|---|---|---|---|---|---|---|---|
| Demographic variables | | | | | | | |
| Child age in years at Time 1 | 243 | | 6 | 5.41 | 0.33 | 4.8 | 6.4 |
| Gender | 256 | | 1 | | | | |
| Male = 1 | 119 | 46 | | | | | |
| Female = 0 | 137 | 54 | | | | | |
| Ethnicity | 243 | | 6 | | | | |
| African American/Black | 213 | 88 | | | | | |
| Hispanic/Latino | 19 | 8 | | | | | |
| Caucasian/White/other | 11 | 4 | | | | | |
| Free/reduced lunch | 236 | | 9 | | | | |
| Yes = 1 | 226 | 96 | | | | | |
| No = 0 | 10 | 4 | | | | | |
| Maternal education | 235 | | 9 | | | | |
| High school or more = 1 | 173 | 74 | | | | | |
| Less than high school = 0 | 62 | 26 | | | | | |
| Treatment condition | 259 | | 0 | | | | |
| Treatment = 1 | 158 | 61 | | | | | |
| Control = 0 | 101 | 39 | | | | | |
| Other variables | | | | | | | |
| HTKS Time 1 | 253 | | 2 | 15.50 | 16.76 | 0 | 57 |
| HTKS Time 2 | 217 | | 16 | 32.04 | 17.01 | 0 | 59 |
| HTKS Time 3 | 171 | | 34 | 40.64 | 16.12 | 0 | 60 |
| VMI Time 1 | 252 | | 3 | 12.96 | 2.30 | 3 | 18 |
| VMI Time 2 | 217 | | 16 | 15.41 | 2.01 | 11 | 21 |
| VMI Time 3 | 171 | | 34 | 16.96 | 2.31 | 12 | 26 |
| LWID Time 1 | 252 | | 3 | 12.00 | 5.22 | 1 | 39 |
| LWID Time 2 | 217 | | 16 | 23.63 | 7.99 | 6 | 56 |
| LWID Time 3 | 171 | | 34 | 34.55 | 7.83 | 14 | 54 |
| AP Time 1 | 252 | | 3 | 12.21 | 3.57 | 0 | 23 |
| AP Time 2 | 218 | | 16 | 18.05 | 4.08 | 6 | 36 |
| AP Time 3 | 171 | | 34 | 23.06 | 4.01 | 11 | 39 |

*Note*: Time 1 = kindergarten entry; Time 2 = first grade entry; Time 3 = second grade entry.

requires students to identify letters followed by progressively challenging words. The AP subtest requires students to solve math problems that increase in difficulty. For each item, scores range from 0 to 1; incorrect responses receive a 0, and correct responses receive 1 point. The student must get six incorrect answers in a row to discontinue the subtest. The child's overall ability is assessed by summing the number of correct answers. Raw scores were used in data analyses.

### Analytic Approach

All analyses were conducted using Stata 14.2 (StataCorp, 2016). An auto-regressive, cross-lagged (ACL) model, based in a structural equation modeling (SEM) framework, was fit to the longitudinal data to simultaneously test multiple predictive associations among EF, VMI, and achievement (literacy and math) across three time points. The time-lags for all variables included in the model were constant among participants. Any path between any two variables across time points was estimated and unconstrained. Additionally, covariances between the residuals of each variable were allowed within each time point for all time points. The model was fully recursive in that paths directed only forward in time, and any variable assessed at an earlier point in time was used to predict all later variables. The fit of the model was assessed using the following criteria: Tucker–Lewis index (TLI) and comparative fit index (CFI) greater than 0.95, and root-mean-square error of approximation (RMSEA) less than or equal to 0.06 (Hu & Bentler, 1998). In order to account for missing data (see Table 1), the full information maximum likelihood (FIML) estimation method was used to obtain more efficient, less biased estimates than simple deletion methods (Enders, 2010).

## RESULTS

Table 1 provides descriptive statistics, including means and standard deviations for all variables included in the study. The increase in missing data across time reflects the transience that occurs with greater frequency in low income communities. Descriptive results reveal participants demonstrated EF levels 1–2 *SD* below age-matched comparisons at kindergarten entry but score gaps narrow by first grade (Ponitz, McClelland, Matthews, & Morrison, 2009). Performance on the VMI was between

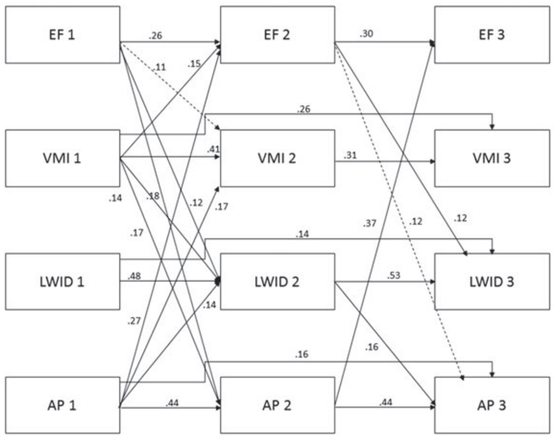


**Fig. 1.** Cross-lagged model depicting the relations among executive function (EF), visuomotor integration (VMI), letter–word identification (LWID), and applied problems (AP) across 3 years. *Note*: Model fit: $\chi^2 = 8.07$, $p = .78$; root-mean-square error of approximation (RMSEA) = 0.00; comparative fit index (CFI) = 1.00; Tucker–Lewis index (TLI) = 1.03; covariates: age, sex, maternal education, treatment condition for unrelated larger study. Time 1 = kindergarten entry; Time 2 = first grade entry; Time 3 = second grade entry.

.5 and .1 *SD* below age-matched comparisons across all three assessment windows (Beery et al., 2010). Children performed on age level across all 3 years in LWID but nearly one year below age-matched norming samples for AP across all three assessment windows (Woodcock et al., 2001).

Figure 1 reports cross-lagged associations among EF, VMI, and math (AP) and reading achievement (LWID) from kindergarten entry to second grade entry. Fit indices report a good model fit: $\chi^2 = 8.07$, $p = .78$; RMSEA = 0.00; CFI = 1.00; TLI = 1.03. Covariates, including age, sex, maternal education, and treatment condition were modeled but not graphically represented. EF at kindergarten entry predicted EF, LWID, and AP in first grade and EF in first grade predicted EF and LWID in second grade. VMI at kindergarten entry predicted EF, VMI, LWID, and AP in first grade but VMI in first grade only predicted VMI in second grade. LWID at kindergarten entry only predicted LWID at first grade and LWID at first grade predicted LWID and AP at second grade. Finally AP at kindergarten predicted EF, VMI, LWID and AP at first grade and AP at first grade predicted EF and AP at second grade.

## DISCUSSION

Congruent with prior research, EF at multiple time points predicted future reading and math achievement (Best et al., 2011). Cross-lagged models revealed bidirectional associations among math and future EF and VMI skills. Interrelations may be explained by common neural pathways. The prefrontal cortex is activated during EF tasks and VMI tasks mainly activate the parietal lobe, whereas both frontal and parietal lobes may be engaged to solve math problems (see Ansari, 2008 for a review). Gray matter mass development in frontal and parietal lobes tends to be delayed for children living in poverty (Hanson et al., 2013) and descriptives for our sample suggest mild to moderate delays in EF, VMI, and math achievement compared to normative samples. Nonetheless, the interrelations among EF, VMI, and math observed in other studies (e.g., Kim et al., 2017) are also observed in our high-risk sample.

Cross-lagged associations between reading and math follow a “learning to read then reading to learn” pattern whereby early math skills support letter and word decoding (i.e., symbolic representation; Lerkkanen et al., 2005). Subsequently, children increasingly rely on reading comprehension in math content areas. Word problems and written instructions both features prominently by second grade.

VMI at kindergarten predicted first-grade skills (slightly better than EF for early literacy), and subsequently did not predict future achievement. Findings from the present study suggest timing may be an important factor to consider if early VMI and EF interventions are developed with the aim of narrowing the achievement gap for children living in poverty. Both foundational skills are malleable and can be trained (Diamond & Lee, 2011; Uttal, Meadow, et al., 2013). Patterns of associations among VMI and achievement detected in early childhood (Cameron et al., 2012; Verdine et al., 2014) did not hold in the elementary school years, although other work with more diverse (lower risk) samples and more complex visuospatial tasks continue to demonstrate relations between VMI and math through second grade (Kim et al., 2017). Two possible explanations are proposed. First, it may be that VMI skills that support achievement reach a threshold whereby additional skill development does not translate into further academic gains. Perhaps children reach a certain level of automaticity (as with learning to reproduce letter and number symbols accurately and efficiently) at which point the threshold for VMI support of achievement gains is reached. Alternatively, perhaps VMI skills need to be further developed in order to continue to support learning. VMI skills in our sample hovered close to one *SD* below national averages; if more cognitively complex visuospatial skills were bolstered, perhaps we would see continued support of achievement trajectories across many years of schooling (Cragg, Keeble, Richardson, Roome, & Gilmore, 2017; Uttal, Miller, & Newcombe, 2013).

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