Educational Research Review 35 (2022) 100412

Contents lists available at ScienceDirect

Educational Research Review

journal homepage: www.elsevier.com/locate/edurev

Meta-analysis on the relation between visuomotor integration and academic achievement: Role of educational stage and disability

Lora Khatib [a], Yaoran Li [a,*], David Geary [b], Vitaliy Popov [c]

[a] Jacobs Institute for Innovation in Education, University of San Diego, San Diego, USA
[b] Department of Psychological Sciences, University of Missouri, Columbia, USA
[c] Department of Learning Health Sciences, University of Michigan, Ann Arbor, USA

ARTICLE INFO

Keywords:
Visuomotor integration
Academic achievement
Mathematics
Reading
Meta-analysis

ABSTRACT

Visuomotor integration (VMI) is the ability to coordinate visual perception and motor functioning. Measures of VMI are commonly used to assess children's readiness for academic learning. Attention and investments towards VMI development are mainly focused on early learners, but some empirical research indicates sustained relations between VMI and academic achievement through middle and high school. To determine the relations between VMI and academic achievement, as well as moderating factors, we conducted a multilevel meta-analysis using a total of 96 articles and 266 effect sizes published over the past 60 years. The pooled effect size revealed moderate correlations between VMI and mathematical (r = 0.39) and reading (r = 0.34) achievement. Educational stage, disability, and intelligence were significant moderators of the relation between VMI and mathematics achievement, whereas educational stage and subdomains of reading skills were significant moderators of the relation between VMI and reading achievement. Implications and future research directions are discussed.

1. Introduction

Visuomotor integration (VMI) is defined as the ability to coordinate visual perception and motor functioning (Beery & Beery, 2006). VMI develops as part of a broader system that includes proprioception (i.e., awareness of body position), visual information processing, and motor movements (Bullock, Grossberg, & Guenther, 1993; Guigon & Baraduc, 2002). These competencies are critical to many everyday activities, such as using utensils to eat or tying one's shoes. Many academic competencies are also supported by visuomotor abilities, as in children's use of fingers to count or add or during the act of handwriting (Brissiaud, 2011; Longcamp, Richards, Velay, & Berninger, 2016). VMI also predicts academic achievement more broadly, independent of IQ and executive functions (Sortor & KULP, 2003; Verdine, Irwin, Golinkoff, & Hirsh-Pasek, 2014). Consequently, measures of VMI are often used to assess children's school readiness.

There are multiple theories as to why VMI may set the stage for, or at least be a good indicator of, children's academic development. One proposal is that the many skills captured by measures of VMI, such as comprehending instructions, focusing attention on a task, and holding and manipulating writing utensils, overlap with the skills needed for success in school settings (Cameron et al., 2015). More directly, the development of many important skills that support academic development are directly influenced by visual-motor integration skills (Dawson & Watling, 2000); these would range from early writing to the mapping of x,y pairs to the coordinate plane.

* Corresponding author. Mother Rosalie Hill 259, University of San Diego, San Diego, CA, 92126, USA.
E-mail address: liyaoran@gmail.com (Y. Li).

https://doi.org/10.1016/j.edurev.2021.100412
Received 30 November 2020; Received in revised form 25 June 2021; Accepted 4 November 2021
Available online 17 December 2021
1747-938X/© 2021 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

It has been suggested that strong visuomotor integration skills facilitate the acquisition of handwriting skills that in turn reduces the need to focus attention on the act of writing. The reduced attentional demands free working memory resources that can then be devoted to written content (Carlson, Rowe, & Curby, 2013).

1.1. How VMI is assessed

Copying figures or drawings is considered an apt measure of VMI, as it can be used to assess the fidelity of the integration of visual information processing and motor coordination (Beery & Beery, 2006). Thus, the most commonly used methods to assess visuomotor integration are design copy tasks that typically require the child to copy increasingly complex figures. The Beery Developmental Test of Visual-Motor Integration (VMI) and the Bender Gestalt Test of Visuomotor Integration are among the most often used measures of VMI (Beery, Buktenica, & Beery, 1997; Bender, 1938). Although the vast majority of studies use design copy tasks, other measures of VMI exist, such as the Grooved Pegboard Test in which the test taker is required to rotate a peg with a key on one side to match and insert it into a small hole (Memisevic, 2019). Accordingly, we assessed whether the type of assessment moderated the relation between VMI performance and academic achievement.

1.2. VMI, Mathematics achievement and educational stage

There are several ways in which visuomotor integration might contribute to mathematical development at different educational stages. The first is the early development of counting competencies and the use of finger representations for facilitating the learning of some numerical concepts (Berch et al., 2015). The process of enumerating (i.e., counting a group of objects) typically involves pointing at each object as it is counted, which helps children keep track of the objects that have been counted and those that remain to be counted (Fuson, 1988; Gelman & Gallistel, 1978). This process contributes to an early understanding of the cardinal value of number words, which in turn, is critical for further growth in number and arithmetic skills (Chu, vanMarle, Rouder, & Geary, 2018; Geary & vanMarle, 2018) and predicts later readiness for learning mathematics at school entry (Geary & vanMarle, 2018). Later in their development, children often use their fingers to represent quantities to be added, and sometimes subtracted, and move the uplifted fingers in sequence while counting (often aloud) to arrive at an answer (Berch et al., 2015; Siegler & Robinson, 1982). Geary and Burlingham-Dubree (1989) found that the sophistication of the mix of strategies used to solve arithmetic problems was related to children's visuospatial abilities.

Further, there is evidence that using manipulatives in early education, often described as "hands-on learning", can lead to a better understanding of mathematical concepts. In a longitudinal study, Guarino, Dieterle, Bargagliotti, and Mason (2013) found that using counting manipulatives (i.e., tangible objects used to count such as pennies or blocks) improves achievement in Kindergarteners. Additionally, a recent meta-analysis found small to moderate advantages with the use of manipulatives in children's learning as compared to use of abstract math symbols (Carbonneau, Marley, & Selig, 2013). Findings that suggest the use of kinesthetic approaches can sometimes facilitate students' understanding of some areas of mathematics provides further evidence that visuomotor integration may be related to academic achievement (Carbonneau et al., 2013; Guarino et al., 2013).

Interestingly, the early use of finger and gesture representation of numbers has created a connection between fingers and representation of numbers and quantitative relations that continues into adolescence and adulthood (Andres, Ostry, Nicol, & Paus, 2008; Fischer, 2008). Studies have shown that hand configurations are associated with adults' numerical representation (Andres et al., 2008; Fischer, 2008). For instance, Andres et al. (2008) tested the influence of the magnitude of a number on grip aperture (i.e., the distance between the finger and the thumb). When labeling the face of an object with a number, it was found that during the initial phases of reaching for the object, higher values led to a larger grip aperture. The grip aperture was adjusted to the size of the object during the second half of reaching towards the object, suggesting that the information relating to the number was processed during the planning stage of the motor movement (Andres et al., 2008). Researchers of embodied cognition also proposed gesturing as an integral tool of investigating, representing, and understanding mathematical ideas (Alibali & Nathan, 2012; Núñez, 2008). For example, Cooperrider, Gentner, and Goldin-Meadow (2016) found that adults tend to use gestures in their explanations when reasoning about relational systems which are prevalent in mathematics. Alibali and Nathan (2012) found that both students and teachers regularly produced gestures when they were trying to explain mathematical concepts and ideas.

Although these studies have found relations between certain aspects of VMI (e.g., finger and gesture representation) and academic achievement throughout development and into adulthood (Andres et al., 2008; Berch et al., 2015; Fischer, 2008; Siegler & Robinson, 1982), it is unclear whether the magnitude of these relationships changes over time. Thus, the correlations between VMI and achievement were examined at different educational stages (e.g., elementary school, secondary school) to determine if educational stages are a significant moderator of this relationship.

1.3. VMI, reading achievement, and educational stage

The relation between VMI and reading outcomes has not been as consistently found as that between VMI and mathematics outcomes. Nevertheless, significant correlations between reading outcomes and VMI have been reported in multiple studies (Bellocchi et al., 2017; Becker, Miao, Duncan, & McClelland, 2014; Hammil, 2004; Sortor & KULP, 2003), although many other studies have found no correlation (Carlson et al., 2013; Goldstein et al., 1994; Morgenstern & McIvor, 1973; Santi, Francis, Currie, & Wang, 2015). Further, there is a lack of evidence relating to how VMI may affect reading development during different educational stages.

Despite these mixed results and gaps in the literature, there is reason to believe that both the visual perception and motor functioning aspects of VMI may contribute to young students' reading skill development. For instance, in a longitudinal study, Franceschini, Gori, Ruffino, Pedrolli, and Facoetti (2012) found that poor reading skills in grades 1 and 2 could be predicted by earlier impaired visual search performance that was measured by the ability to identify a target surrounded by distractors and spatial cueing facilitation (i.e., the ability to discriminate the orientation of a stimulus). Further, Pham and Hasson (2014) found visuospatial working memory to be a significant predictor of reading ability; a related study found that visuospatial attention predicted word reading accuracy and mathematics achievement (Geary, Hoard, Nugent, Ünal, & Scofield, 2020). There is also evidence that fine motor skills predict reading achievement (Iversen, Berg, Ellertsen, & Tonnessen, 2005; Son & Meisels, 2006). Son and Meisels (2006) found that strong fine motor skills in Kindergarten predicted first grade reading achievement. Further, Iversen et al. (2005) compared a group of children with dyslexia, children identified as poor readers, and children identified as proficient readers on a series of motor tasks. They found over 50% of children in the dyslexic and poor reading groups showed conclusive motor coordination difficulties. It is not clear, however, whether such results reflect a direct relation between VMI and reading abilities or if the relation is due to a third factor, such as brain maturation.

VMI may be fundamental to handwriting, given the latter is dependent on the ability to integrate visual perception and motor functioning (Longcamp et al., 2016; Volman, van Schendel, & Jonmans, 2006; Weintraub & Graham, 2000). Indeed, handwriting is the integration of VMI with aspects of language, including language sounds and comprehension, and many of these same language abilities are engaged during the act of reading (Longcamp, Zerbato-Poudou, & Velay, 2005; Medwell & Wray, 2014). More specifically, because handwriting requires close attention to the form of letters and words, handwriting supports pattern recognition that can lead to a more fluent recall of letters and words when reading as a young child (Waterman, Havelka, Culmer, Hill, & Mon-Williams, 2015). In other words, VMI may influence reading, at least in part, through handwriting, since the ability to handwrite may lead to improved fluency in letter-word identification. This was shown in a study by Longcamp et al. (2005) in which two groups of young children were trained to copy letters by typing or handwriting them. The children who were taught to handwrite exhibited greater letter recognition than the children who were taught to type (Longcamp et al., 2005). On the basis of these findings, a relation between VMI and reading achievement could emerge at a young age.

At the same time, the relation between VMI and other reading competencies, such as comprehension, are not well understood. Further, the relation between VMI and reading performance is not well understood across educational stages. A better understanding of this relationship would shed light on how VMI is linked to reading development and what populations would benefit most from strengthening the VMI skills that might contribute to reading development. Accordingly, the present study examines the relation between VMI and reading development across educational stages, disability factors, and reading outcomes (e.g., reading comprehension versus letter-word identification).

1.4. VMI and intelligence in predicting academic achievement

Intelligence is a potential confounding factor that contributes to the relations between VMI and academic achievement. Intelligence is a consistent predictor of individual differences in mathematics achievement as well as longitudinal gains in achievement (Bull & Lee, 2014; Deary, Strand, Smith, & Fernandes, 2007; Geary & vanMarle, 2018; Lee & Bull, 2016). The same is true for reading achievement (McCoach, Yu, Gottfried, & Gottfried, 2017; Naglieri & Ronning, 2000; Peng, Wang, Wang, & Lin, 2019). Criticisms of the empirical relation between VMI and academic achievement have highlighted evidence that students with intellectual disabilities not only exhibit problems that affect academic learning such as, perceiving and processing new information, flexible thinking, and applying knowledge to solving problems (Henry Bettenay, & Carney, 2011); but also often exhibit problems that affect visuomotor integration such as delayed motor functioning and sensorimotor dysfunction (Memisevic & Sinanovic, 2012; Wuang, Wang, Huang, & Su, 2008).

Intelligence Quotient (IQ) tests are used to measure intellectual abilities. In attempts to address this issue, multiple studies have found VMI to be a unique predictor of mathematical achievement when controlling for IQ (Carlson, 2013; Goldstein, 1994; Morgenstern, 1973; Sortor, 2003; Taylor, 1999). On the other hand, a few studies have found that VMI is no longer related to reading achievement once IQ is controlled (Carlson, 2013; Goldstein, 1994; Morgenstern, 1973). Here, we assessed the relation between VMI and academic achievement across groups with different levels of intelligence to assess the extent to which IQ might moderate the relation between VMI and academic achievement.

1.5. Present study

Prior findings have shown that VMI is correlated with and is a predictor of academic achievement and longitudinal gains in achievement (Cameron et al., 2015; Carlson et al., 2013; Sortor & KULP, 2003; Verdine et al., 2014). We extend these findings with a multilevel meta-analysis of the relation between VMI and academic achievement, with the goal of determining if these relations vary across reading and mathematics achievement and their subdomains (e.g., reading fluency, arithmetic), and to determine if the strength of the relations varies across educational stages (i.e., early childhood, elementary education, secondary education).

Even though tests of VMI are often used to assess school readiness and academic performance, the unique relations between VMI and such outcomes are not fully understood or systematically reviewed. More specifically, the relations between VMI and academic outcomes in later educational stages and for students with different disabilities (e.g., mental disability vs. learning disability) have not been fully explored or reviewed. Educational stage and disability thus are the key potential moderators of interest. As noted, domain-general cognitive abilities, such as IQ, are potential confounding factors or might moderate the strength of the relation between VMI and academic outcomes.

To our knowledge, no meta-analyses on the relations between visuomotor integration and academic achievement exist to date. The present study used a multilevel meta-analytic approach to systematically explore the relations between VMI and mathematics and reading outcomes across educational stages and with consideration of the potential influences of IQ and disabilities on the strength of the relationship between VMI and academic outcomes. These findings can be used to highlight the importance of measuring visuomotor integration at an early age, and to identify populations that would benefit most from visuomotor integration interventions.

2. Methodology

2.1. Study selection

This meta-analysis was conducted based on guidelines proposed by Quintana (2015). A two-step screening process implemented by two independent researchers was used to extract studies from PsychINFO, Web of Science, ERIC, and OVID [journals@OVID, MEDLINE, and Health and Psychosocial Instruments (HAPI)]. Terms were searched for in titles, abstracts, or keywords and the search was restricted to studies with samples of ages 18 and under when possible. The terms used to identify potentially relevant studies included: visual motor, visual-motor, visuomotor, math*, arithmetic, numeracy, academic achievement, read*, and literacy. The combined search yielded a total of 2,229 studies after 408 duplicates were removed.

After searches were implemented, two independent researchers screened titles and abstracts to determine whether full texts should be retrieved. Lists of relevant studies were compared and any disagreements were discussed. A total of 202 full texts were retrieved. The two researchers then further screened the reports based on the inclusion/exclusion criterion shown in Table 1. After comparing the lists of the two reviewers and resolving disagreements, 96 studies (266 effect sizes, 111,138 participants) met the inclusion criteria.

2.2. Data extraction and coding

Information from each study was extracted to perform the analysis. The variables coded include: (1) year the study was published, (2) type of report (e.g., dissertation), (3) sample size, (4) participant demographics (i.e., disabilities, age/educational stage, gender, mean IQ, income, country), (5) instruments used to measure visuomotor integration, reading, and mathematics (6) mathematics and reading outcome subdomains (e.g., arithmetic, comprehension), and (7) effect sizes.

2.3. Moderators

Moderators were categorized into three groups: report variables (type, year), participant demographics and backgrounds (educational stage, disability, Intelligence/IQ, and country), and measures (VMI assessment, math and reading subcategory, and math and reading measurement).

2.3.1. Report variables

Reports were coded for type and year as displayed in Table 2. Non-peer reviewed publications (e.g., dissertations) were included to decrease the risk of publication bias. To ensure there were no differences in effect sizes due to the type of report, this was tested as a moderator. The number and sample sizes of studies that investigated the relations between VMI and achievement increased notably in the past two decades. The year of report was included as a moderator to test whether methodological or instructional changes throughout the years affect the relationship between VMI and academic achievement.

2.3.2. Participant demographics and backgrounds

Participant demographics included educational stage, disability status, mean IQ, gender, income, ethnicity, and continent. However, it is not possible to assess potential moderation effects for gender, income, and ethnicity because very few separate effect sizes were reported across these groups. Participant demographics are shown in Table 3. Income is not shown because it was not reported in 66 studies (67% of participants) and the studies that did report it used heterogeneous measures that were not comparable.

Participants' educational stages were coded from studies reporting either one, some, or all of the following measures: mean age, age range, and grade level. Studies were subcategorized into three groups based on the available information. "Early childhood" included studies in which participants were in Kindergarten or earlier, or 6 years of age and younger, or in early childhood education. These children are often referred to as early learners. "Elementary" included studies in which participants were in first through fifth grade or

Table 1
Inclusion and exclusion criteria for screening relevant studies.

Criteria	Inclusion	Exclusion
Language	English	Non-English Language
Availability	Full-text available	Studies not accessible by public or University database
Variables	The study measured visuomotor integration and mathematical or reading achievement	Study does not measure visuomotor integration and either mathematical or reading achievement
Statistical Information	Contains information of effect size or the effect size can be derived	Observational or case studies that only provide qualitative information
Measurement	Measures of visual motor integration include visual and motor processing	Measurements includes only factors of VMI such as visual spatial or fine motor separately

Table 2
Study variables.

Type of report	Number of Reports	Participants (N)	Participants (%)
Conference paper	2	86	0.1%
Dissertation	10	2,384	2.1%
Journal	78	107,684	96.9%
Report	6	984	0.9%
Year of report	**Number of Reports**	**Participants (N)**	**Participants (%)**
1961 to 1980	23	7,906	7.1%
1981 to 2000	21	3,656	3.3%
2001 to 2020	52	99,576	89.6%

Table 3
Participant demographics.

Gender	Number of Reports	Participants (N)	Participants (%)
Male		43,999	39.6%
Female		43,515	39.2%
Unreported		23,624	21.3%
Educational Stage Group	**Number of Reports**	**Participants (N)**	**Participants (%)**
Early Childhood	29	24,751	22.3%
Elementary	50	83,154	74.8%
Secondary	12	1,706	1.5%
Variety of age groups	11	1,527	1.4%
Ethnicity	**Number of Reports**	**Participants (N)**	**Participants (%)**
White		13,440	12.1%
Black or African American		4,560	4.1%
Hispanic/Latino		3,146	3.8%
Asian		308	0.3%
Other/Mixed		303	0.3%
Unreported		89,381	80.4%
Disability	**Number of Reports**	**Participants (N)**	**Participants (%)**
Learning Disability	14	2,473	2.2%
Mental Disability	9	894	0.8%
Physical Disability	11	3,785	3.4%
Typical Development	64	103,986	93.6%
Mean IQ	**Number of Reports**	**Participants (N)**	**Participants (%)**
Low (40th percentile and below)		1,521	1.4%
Average (41st percentile to 59th percentile)		3,332	3.0%
High (60th percentile and above)		1,693	1.5%
Unreported		104,592	94.1%
Continent	**Number of Reports**	**Participants (N)**	**Participants (%)**
North America (U.S.)	74	104,904	94.4%
Europe	13	3,933	3.5%
Asia	4	538	0.5%
Africa	3	1,513	1.4%
Oceania	2	250	0.2%

ages 7–10 years, inclusive. "Secondary" included studies in which participants were in 6th to 12th grade or 11 years or older, inclusive. Educational stage was tested as a moderator to determine if the relations between VMI and academic achievement fluctuates throughout development.

Disabilities were categorized into learning, physical, and mental disabilities. Samples were categorized as learning disabled if they contained participants who were reported to have a general learning disability or a specific learning disability (e.g., dyslexia, reading, or math disability). Physical disabilities were samples containing participants who had a physical illness or disorder, such as acute lymphoblastic leukemia or developmental coordination disorder. Mental disabilities were samples in which participants were diagnosed as intellectually disabled or having autism spectrum disorder. Disability and IQ were included as moderators because these are consistently related to academic achievement and thus may have an influence on the strength of the relation between VMI and academic achievement. Samples with typical and atypical groups were separated in the analyses and treated as different samples, accounting for within-study variance, using the multilevel meta-analysis approach.

We also collected information on the country in which the study took place. Because multiple countries only had 1 effect size reported, countries were categorized by continent. The continent of which participants resided was tested as a moderator to examine whether curricular and language differences between countries could influence the correlation between VMI and academic achievement.

2.3.3. Assessments

The type of assessments used to measure VMI, mathematics, and reading was also noted and tested as a moderator to determine whether effect sizes between VMI and academic achievement differed across measures.

2.3.3.1. Visuomotor integration. The assessments used to measure visuomotor integration are shown in Table 4. The majority of studies used the Bender Gestalt Test of Visuomotor Integration (Bender, 1938) and the Developmental Test of Visuomotor Integration (Beery, 1989).

2.3.3.2. Mathematics and reading achievement. A variety of assessments were used to measure mathematics and reading achievement. The most common ones were subtests of the Woodcock Johnson Tests of Achievement (WJ) (Woodcock, 1977), Wide Range Achievement Test (WRAT) (Jastak & Wilkinson, 1984), Gates-MacGinitie Reading Test (MacGinitie, 1978), California Achievement Test (CAT) (Tiegs & Clark, 1977), Wechsler Individual Achievement Test (WIAT) (Wechsler, 2005), and Stanford Achievement Test (SAT) (Psychological Corporation, 2002). Assessments were subcategorized into standardized assessments, researcher developed measures, and teacher's ratings/grading reports as shown in Table 5 and Table 6. Intelligence/IQ assessments are summarized in Table 7.

2.3.4. Mathematics and reading subdomains

A number of studies decomposed reading and mathematics achievement into more specific subdomains or competencies, such as arithmetic or reading comprehension. These subdomains were tested as moderators to determine whether effect sizes between VMI and achievement differ per specific categories. These are shown in Table 8 for mathematics and Table 9 for reading.

3. Statistical analysis

A total of 96 reports and 266 effect sizes were included in the meta-analysis. Two separate multilevel meta-analyses for mathematics and reading achievement were conducted using the 'metafor' package in R Studio (Viechtbauer, 2010). A total of 71 reports and 129 effect sizes were included in the meta-analysis of the relation between mathematics achievement and VMI, and 78 reports and 137 effect sizes for the reading achievement and VMI analysis.

Multiple studies reported more than one effect size based on moderators such as age, achievement measures, and so forth. Forty-nine reports produced 150 effect sizes from the same sample. These dependent effect sizes are common issues in meta-analyses and a variety of methods have been developed to resolve them. We used Polanin's (2014) 3-level method to avoid "double-counting" studies in a multilevel meta-analysis. The method adjusts the variance within each study based on the number of reported effect sizes, while maintaining the separation between moderators. Thus, the "first level" accounts for the variability in the sampling error of each individual study, the "second level" accounts for the variability within studies due to multiple effect sizes nested into a single study, and the "third level" accounts for the variability at the between-study level.

Correlation coefficients between the subjects' mathematics and reading outcomes and VMI scores were used as the effect sizes. This is because the majority of studies reported Pearson's correlation coefficients to describe the relationship between VMI and academic achievement. A total of 18 effect sizes were reported in statistics other than correlation coefficients, such as means or beta coefficients. These effect sizes were transformed into correlation coefficients based on statistical methods proposed by Borenstein, Hedges, Higgins, and Rothstein (2011).

Studies that used the Bender Gestalt Test reported negative correlations because this test is scored by the number of errors. All other

Table 4
Visuomotor integration assessments.

VMI Assessment	Number of Reports	Participants (N)	Participants (%)
Developmental Test of Visual-Motor Integration (VMI) Beery	51	18,962	22.4%
Bender Gestalt Test of Visuomotor Integration	26	5,139	6.1%
Copy Design Task	3	4,801	5.7%
Rey-Osterrieth Complex Figure	3	1,298	1.5%
Grooved Pegboard Test	2	350	0.4%
Design Copying subtest of the NEPSY	2	1,480	1.7%
Developmental Test of Visual Perception-2: VMI quotient	2	612	0.7%
Bruininks–Oseretsky Test of Motor Proficiency	1	62	0.1%
Kindergarten Diagnostic Instrument	1	281	0.3%
LAP-D (VSI component of fine motor)	1	50,805	60.0%
Minnesota Percepto-diagnostic Test	1	203	0.2%
The Bicycle Drawing Test	1	164	0.2%
Visuomotor Accuracy Tracking (VAT)	1	423	0.5%
Wide Range Assessment of Visual Motor Abilities (WRAVMA)	1	66	0.1%

Table 5
Mathematic assessments.

Mathematic Assessment	Number of Reports	Participants (N)	Participants (%)
Researcher developed assessments	4	595	0.6%
Standardized assessments	60	98,173	98.3%
Teacher's ratings/Grading reports	5	1,152	1.2%

Table 6
Reading assessments.

Reading Assessment	Number of Reports	Participants (N)	Participants (%)
Researcher developed assessments	6	1,059	1.0%
Standardized assessments	70	98,905	98.0%
Teacher's ratings/Grading reports	4	935	0.9%

Table 7
Intelligence/IQ assessments.

Intelligence/IQ Assessment	Number of Reports	Participants (N)	Participants (%)
Wechsler Intelligence Scale for Children (WISC)	22	3,083	56.5%
Stanford Binet Intelligence Scales	5	668	12.2%
Wechsler Preschool and Primary Scale of Intelligence (WPPSI) subtests	5	245	4.5%
Peabody Picture Test	3	356	6.5%
Slosson Intelligence Test	3	216	4.0%
Kaufman Brief Intelligence Test	2	82	1.5%
Primary Mental Abilities Test	1	58	1.1%
Raven's Standard Progressive Matrices	1	28	0.5%
Otis Quick-scoring Mental Ability Tests	1	203	3.7%
Lorge-Thorndike Intelligence Test	1	242	4.4%
Columbia Mental Maturity Scale (CMM)	1	122	2.2%
Cognitive Abilities Test	1	153	2.8%

Table 8
Mathematics categories.

Mathematics Categories	Number of Reports	Participants (N)	Participants (%)
Arithmetic	21	7,237	72.0%
Geometry & Measurement	2	324	3.2%
Applied Math problem solving	6	2,486	24.7%

Table 9
Reading categories.

Reading Categories	Number of Reports	Participants (N)	Participants (%)
Reading Comprehension	14	7,019	44.0%
Letter-word Identification	8	1,604	10.0%
Vocabulary	7	2,777	17.4%
Reading Fluency	8	4,561	28.6%

assessments are scored by the number correct; therefore, correlations based on the Bender Gestalt Test were reversed by multiplying by −1. Correlation coefficients were transformed to fisher's Z scores with corresponding variances. The overall effect sizes and variances were then calculated and transformed back to Pearson's *r* for reporting. Effect sizes were interpreted as small, moderate, or large using Cohen's guidelines (Cohen, 1992).

Funnel plots were used to assess risk of publication bias using Egger's test of the intercept (Egger, Smith, Schneider, & Minder, 1997). Standardized methods to assess for publication bias have not been established for multilevel meta-analyses. Therefore, a random-effects model was used to assess for bias following procedures similar to those used by Kredlow, Unger, and Otto (2016). Trim and fill procedures proposed by Shi and Lin (2019) were conducted to estimate the number of studies missing on the left of the funnel plot to make it symmetrical and to yield a new effect size correcting for publication bias.

Lastly, moderators were tested individually. All moderator analyses were computed using a meta-regression model where the sub-group was inputted as a predictor. This determined if effect sizes differed across groups (see Harrer M. et al., 2019). All moderators were computed as categorical variables except for IQ which was computed as a continuous variable. Moderators were categorized into sub-groups because different metrics (e.g., age vs. grade) were often used across studies. For example, educational stage was tested as a categorical variable since some studies reported the median age of the sample while others reported grade level. IQ was the only moderator in which this was not an issue and was therefore left as a continuous variable. When a significant moderator was identified, a separate meta-analysis was conducted for each subgroup as ad-hoc analyses to better understand which groups significantly differed from each other. When a group had multiple effect sizes reported within a study, a multilevel meta-analysis was deployed. When there were less than three effect sizes in a subgroup, the average effect sizes of these studies were reported instead.

4. Results

4.1. Mathematics and visuomotor integration

The multilevel meta-analysis derived from the 129 effect sizes and 71 studies yielded a moderate correlation between mathematical achievement and visuomotor integration ($r = 0.39, p < .0001$). Q-tests for heterogeneity revealed significant variance around the mean ($Range = 0.01–0.85$; $Q(128) = 1202.43, p < .0001$). Regression tests for funnel plot asymmetry revealed a risk for publication bias ($z = 3.8, p < .001$). Trim and fill procedures estimated 22 missing effect sizes on the left side of the funnel plot ($SE = 7.4$). When correcting for these missing studies, the pooled effect size between VMI and mathematics did not change ($r = 0.39$).

A total of 106 effect sizes were used to analyze the moderating effect of educational stage on the correlation between VMI and mathematical achievement; 23 effect sizes consisted of samples with mixed age groups and these were excluded from this analysis.

Educational stage was a significant moderator of the correlation between mathematics outcomes and VMI ($QM(df = 2) = 38.91$; $p < .0001$, see Table 10). The contrast of the relations between VMI and mathematical achievement in the children in early childhood education ($r = 0.41$) and children in elementary education ($r = 0.35$) was significant ($p < .0001$), but the relations were not different between elementary education students ($r = 0.35$) and secondary education students ($r = 0.52, p = .12$) or between the early childhood group ($r = 0.41$) and secondary education group ($r = 0.52, p = .47$). Notably, the effect sizes varied to a larger extent in the studies of secondary education students, but the smallest effect size reported in the studies was still larger than 0.2.

Three of the 57 effect sizes in the elementary education group and four of the 16 effect sizes in the secondary education group used samples with mental disabilities. After excluding these samples, the effect sizes for the early childhood and elementary education groups remained the same, but the mean effect sizes for the secondary education group decreased to .38 (see Table 11). The educational stage remained a significant moderator of the overall relations between mathematics outcomes and VMI ($QM(df = 2) = 35.98$, $p < .0001$). More specifically, the contrast between early childhood ($r = 0.41$) and elementary education ($r = 0.35$) remained statistically different ($p < .0001$). The contrast between elementary ($r = 0.35$) and secondary ($r = 0.38$) education did not differ ($p = .98$) nor did early ($r = 0.41$) and secondary ($r = 0.38$) education ($p = .69$).

To test whether having a disability is a moderator of the relationship between VMI and mathematics outcomes, groups were categorized into learning, mental, and physical disability and no disability. Moderation analysis of these four groups revealed a significant effect ($QM(df = 3) = 15.1, p = <.005$). As shown by Table 12, there was a stronger relation between VMI and mathematics outcomes for students with mental disabilities ($r = 0.55$) relative to those with physical ($r = 0.43$) and learning ($r = 0.34$) disabilities and their typically achieving peers ($r = 0.35, p = <.05$). When combining the three groups consisting of atypical students (i.e., having a learning, mental, or physical disability) and testing this group against typical students, a moderating effect was found ($QM(df = 1) = 4.01, p < .05$).

We further explored if IQ is a moderator of the relations between VMI and mathematical achievement. We identified 29 studies (48 effect sizes) that reported the sample's mean IQ. A multilevel meta-regression analysis revealed that the mean IQ of the sample inputted into the model as a continuous variable was a significant moderator of the relation between mathematics and VMI ($QM(df = 1) = 7.37, p < .01$). The results suggest lower IQ scores predict stronger correlations between mathematics outcomes and VMI. Table 13 shows the differences in effect sizes between student groups of the top and bottom 50th percentiles.

Neither type of report nor the year of the report was a significant moderator of the relation between mathematics outcomes and VMI ($p = .47$ and $p = .46$, respectively). Moreover, the measures of visuomotor integration and mathematics outcomes and different math sub-domains were not significant moderators of the overall effect size.

With regards to participant demographics, the continent of where the data was collected was a significant moderator of the relation between mathematics outcomes and VMI ($QM(df = 4) = 15.52, p < .01$). However, the large differences between sample sizes across continents should be taken into consideration. Because there were only 4 reports from Asia, the significant influence of the continents on the overall effect size may be due to one study from Saudia Arabia. Here, the sample of participants was diagnosed with a mild intellectual disability and was an outlier ($r = 0.83, p < .001$). After removing this study, the continent of participants was no longer a significant moderator ($p = .36$).

Table 10
Effect sizes of VMI and mathematics achievement by educational stage.

Educational Stage	K	N	Mean Effect Sizes	SE	CI	Range	P-Value
Early Childhood	34	24,751	0.41	0.049	0.35–0.54	0.01–0.67	<.0001
Elementary	57	83,154	0.35	0.038	0.29–0.44	0.01–0.70	<.0001
Secondary	16	1,706	0.52	0.091	0.35–0.71	0.21–0.85	<.0001

K = number of effect sizes; N = overall number of participants per group.

Table 11
Effect sizes of VMI and mathematics achievement by educational stage excluding mental disabilities.

Educational Stage	K	N	Mean Effect Sizes	SE	CI	Range	P-Value
Early Childhood	34	21,804	0.41	0.048	0.31–0.47	0.01–0.67	<.0001
Elementary	55	75,246	0.35	0.038	0.27–0.40	0.01–0.70	<.0001
Secondary	12	1,319	0.38	0.073	0.26–0.54	0.21–0.64	<.0001

K = number of effect sizes, N = overall number of participants per group.

Table 12
Effect sizes of VMI and mathematics achievement by disability.

Disability	K	N	Mean Effect Sizes	SE	CI	Range	P-Value
Learning	10	3,513	0.34	0.070	0.22–0.49	0.09–0.70	<.0001
Mental	12	903	0.55	0.165	0.30–0.94	0.35–0.85	<.005
Physical	19	2,054	0.43	0.063	0.34–0.59	0.01–0.66	<.0001
No Disability	88	93,947	0.35	0.034	0.31–0.44	0.01–0.79	<.0001

K = number of effect sizes, N = number of participants per group.

Table 13
VMI and Math in top and bottom 50th mean IQ percentiles.

IQ	K	N	Mean Effect Sizes	SE	CI	Range	P-Value
Bottom 50th percentile	25	2,603	0.49	0.079	0.369–0.602	0.09–0.85	<.0001
Top 50th percentile	23	3,910	0.39	0.054	0.294–0.472	0.02–0.79	<.0001

K = number of effect sizes; N = overall number of participants per group; Top 50th was 100 points and above. Bottom 50th was 99.99 points and below.

4.2. Reading and VMI

The multivariate meta-analysis derived from 137 effect sizes in 78 reports revealed a moderate correlation between reading outcomes and visuomotor integration ($r = 0.34$, $p < .0001$). Q-tests for heterogeneity revealed significant variance ($Q(136) = 956.80$, $p < .0001$) around the mean effect size. Regression tests for funnel plot asymmetry revealed no risk for publication bias ($z = 1.5$, $p = .15$). Further, trim and fill procedures estimated no studies missing on the left side of the funnel plot ($SE = 6.4$).

An analysis using 124 effect sizes across 70 studies revealed the educational stage as a significant moderator of the relation between VMI and reading outcomes ($QM(df = 2) = 26.1$, $p < .0001$, see Table 14). The correlation was the largest for the early childhood education group ($r = 0.43$) and significantly larger than that found for the elementary education group ($r = 0.32$, $p < .001$). The effect size for the secondary education group ($r = 0.30$) appears to be the lowest among the three groups, however, it did not significantly differ from that of the elementary education students ($r = 0.32$, $p = .20$).

The pooled effect size between age groups is shown in Table 13. When excluding mental disabilities, the educational stage is still a significant moderator ($p < .0001$). Excluding mental disabilities produced little change to the overall effect sizes in each age group (see Table 15).

The same method to analyze disabilities for mathematics was used for reading. There were no overall differences in the effect sizes across disability groups, as shown in Table 16 ($p = .60$). However, the effect size for reading disabilities ($r = 0.45$) was larger than that found for other types of learning disabilities ($p = .04$).

Multi-level meta-analysis testing the moderation effect of mean IQ as a continuous variable was not significant ($QM\ (df = 1) = 0.06$, $p = .81$). The effect size between the top and bottom 50th percentile is shown in Table 17.

Reading categories were decomposed into comprehension, letter-word identification, reading fluency, and vocabulary. The effect sizes differed across these categories (Table 18, $p = .02$). Ad-hoc analyses revealed that the correlation for vocabulary ($r = 0.30$) was statistically different from that for comprehension ($r = 0.39$, $p = .02$) and letter-word identification ($r = 0.40$, $p < .01$), but was not different from reading fluency ($r = 0.34$, $p = .20$). Comprehension ($r = 0.39$) was not different from letter-word identification ($r = 0.40$, $p = .44$) or reading fluency ($r = 0.34$, $p = .19$). Letter-word identification ($r = 0.40$) and reading fluency ($r = 0.34$) were also not statistically different ($p = .88$).

Table 14
Effect sizes of VMI and reading achievement by educational stage.

Educational Status	K	N	Mean Effect Sizes	SE	CI	Range	P-Value
Early Childhood	40	19,334	0.43	0.062	0.33–0.57	0.14–0.87	<.0001
Elementary	74	79,594	0.32	0.029	0.27–0.38	0.03–0.69	<.0001
Secondary	10	1,206	0.30	0.074	0.17–0.46	0.08–0.70	<.0001

K = number of effect sizes, N = number of participants per group.

Table 15
Effect Sizes of VMI and Reading Achievement by Educational Stage excluding mental disabilities.

Educational Status	K	N	Mean Effect Sizes	SE	CI	Range	P-Value
Early Childhood	40	19,334	0.43	0.062	0.33–0.57	0.14–0.87	<.0001
Elementary	72	79,548	0.33	0.029	0.27–0.38	0.03–0.69	<.0001
Secondary	7	869	0.29	0.094	0.11–0.47	0.08–0.70	0.0106

K = number of effect sizes, N = number of participants per group.

Table 16
Effect sizes of VMI and reading achievement by disability.

Disability	K	N	Mean Effect Sizes	SE	CI	Range	P-Value
Learning	11	2,814	0.31	0.079	0.17–0.48	0.07–0.66	<.0001
Mental	11	1,024	0.41	0.073	0.30–0.58	0.20–0.57	<.0001
Physical	12	1,995	0.39	0.077	0.26–0.56	0.11–0.70	<.0001
None	103	95,678	0.33	0.034	0.27–0.41	0.03–0.87	<.0001

K = number of effect sizes, N = number of participants.

Table 17
VMI and Reading in the top and bottom 50th mean IQ percentiles.

IQ	K	N	Mean Effect Sizes	SE	CI	Range	P-Value
Top 50th percentile	29	5,531	0.39	0.080	0.249–0.515	0.13–0.87	<.0001
Bottom 50th percentile	25	2,603	0.39	0.079	0.248–0.520	0.11–0.97	<.0001

K = number of effect sizes, N = overall number of participants per IQ group; Top 50th was 100 points and above; Bottom 50th was 99.99 points and below.

Table 18
Reading effect sizes by reading category.

Category	K	N	Mean Effect Sizes	SE	P-Value
Comprehension	30	7,019	0.39	0.031	<.0001
Letter-word Identification	13	1,604	0.40	0.106	0.0001
Reading Fluency	18	4,561	0.34	0.044	<.0001
Vocabulary	14	2,777	0.30	0.037	<.0001

K = number of effect sizes, N = number of participants per group.

Type and year of report were not significant moderators of the relation between reading outcomes and VMI ($p = .25$ and $p = .31$, respectively). The continent of participants was also not a significant moderator ($p = .96$).

5. Discussion

There are increased efforts to understand the development of students' visuospatial abilities and examine the potential influence of embodied learning approaches on students' academic performance (Abrahamson & Sánchez-García, 2016; DeSutter & Stieff, 2017; Stieff, Lira, & Scopelitis, 2016). Visuomotor integration is crucial to some early aspects of mathematics and writing/reading development, as well as for gesturing (as a means of communicating knowledge), but the relation between VMI and academic outcomes across development is not well understood. The overall results revealed that the correlations between measures of VMI and mathematics ($r = 0.39$) and reading ($r = 0.34$) outcomes were moderate. These relations are found at all ages, but were lower for older students' reading achievement. Also, the meta-analyses revealed that the relations between VMI and mathematics was higher for students with mental disabilities and students of lower IQ, and the relations between VMI and reading was higher for students with reading disabilities, and particularly for comprehension and letter-word identification.

5.1. VMI as a unique indicator of cognitive ability predicting achievement

As was described, measures of VMI are often used as indicators of school readiness (Sulik, 2018), on the assumption that VMI should support handwriting which in turn supports further learning. On the basis of this assumption, it could be that correlations between performance on VMI measures and mathematics and reading achievement are higher for younger than older students. The results provided partial support for this expectation in that the correlation between VMI and academic achievement was higher for preschool/Kindergarten than elementary children for both reading and mathematics.

Studies that were included in this meta-analysis provide some insights into why this might be the case (Cameron, 2015; Duran, 2018; Kim, 2018). In a longitudinal study, Kim, Duran, Cameron, and Grissmer (2018) used the KeyMath-3 Diagnostic Measurements to assess numeration, geometry, and measurement skills in Kindergarteners and first graders. The authors found a reciprocal relationship between VMI and mathematics achievement in Kindergarten but not at the end of first grade. One potential reason is that VMI may be more relevant to solving arithmetic problems with computational strategies, such as counting on fingers to add, rather than to directly retrieving facts from long-term memory. The former will occur more frequently during the early learning of mathematics and the latter more frequently with practice. In other words, when given the same mathematical measures of numeration problems, they may be measuring problem-solving in pre-K settings but fact retrieval for later grades in elementary school.

A similar process might explain the higher correlation between VMI and reading achievement for preschool/Kindergarten than elementary school children. Kindergarteners who start learning to read are essentially using problem-solving strategies and multiple cognitive processes whereas in later grades a word is processed through retrieval rather than being "sounded out." This explanation is supported by the finding of a much stronger correlation between VMI and "letter-word identification" in learners of early childhood education ($r = 0.43$) as compared to learners of elementary education ($r = 0.13$). The pattern also suggests that VMI might contribute more to reading achievement in early learners compared to older ones by facilitating learning how to write letters that in turn facilitates phonemic awareness and early reading abilities. This supports the theory that greater handwriting skills leads to more efficient recognition of different letters and words (Longcamp et al., 2005; Medwell & Wray, 2014; Waterman et al., 2015). It may be the case that as retrieval of letter-sound and word-sound associations becomes more fluent, the benefits of VMI-facilitated writing fade.

Further, we have found that the type of reading task was a significant moderator of the effect size between reading and VMI. Reading fluency and vocabulary correlated less with VMI than comprehension. This stronger correlation with reading comprehension and VMI is potentially explainable based on one of the studies used in this meta-analysis (Santi et al., 2015). The authors of this study underscore the importance of considering different reading components (e.g., phonological awareness and decoding) when examining the relation between reading and visuomotor skills, in which many past studies have failed to do. After controlling for phonological awareness, decoding, and fluency, the relation between comprehension and VMI diminished (see Santi et al., 2015). In other words, reading comprehension is dependent on multiple processes and VMI appears to correlate with one or several of these underlying processes.

As with reading, it has also been suggested that VMI might be more strongly correlated with mathematics achievement in younger than older students. This is because younger students are more dependent on finger representations of quantity or to aid in solving simple arithmetic problems (for reviews see Berch et al., 2015). The use of these strategies was also significantly correlated with spatial subtests of the WPPSI (Geary & Burlingham-Dubree, 1989). Therefore, it is reasonable to assume using fingers to solve math problems may be associated with stronger visuospatial skills. Indeed, we found that VMI was more strongly correlated among younger than elementary students. That said, there were modest but significant correlations between VMI and mathematics achievement throughout schooling, suggesting the relation may go beyond finger counting.

Some neuropsychological and brain imaging studies are consistent with relations between some number and arithmetic competencies and visuomotor skills. In a classic study, Gerstmann (1940) defined a cluster of deficits associated with damage to an area of the parietal cortex, the angular gyrus, and adjacent regions of the occipital lobe. The deficits included difficulties with arithmetic calculation and finger agnosia (i.e., inability to recognize and differentiate different fingers). The calculation difficulties included simple problems (see also Henschen & Schaller, 1925), and a poor understanding of how visuospatial position in multicolumn problems represented different quantities (e.g., 259 + 938, and not understanding that the '5' and '3' represent sets of 10). These findings may point towards overlapping neural mechanisms between VMI and mathematics which may contribute to new methods in fostering such neural mechanisms in children.

Further, many studies have shown visuospatial skills are strongly correlated to mathematical skills in later grades and even among adults (Jarvis & Gathercole, 2003; Li & Geary, 2013, 2017; Maybery & Do, 2003; Reuhkala, 2001; Wei, Yuan, Chen, & Zhou, 2012). This could also provide an explanation for why correlations between early childhood and secondary education students did not differ. Secondary students may be more influenced by visuospatial factors due to the mathematical content (i.e., Geometry) introduced in later grades that requires more spatial thinking than in elementary grades. In a study by Duran, Byers, Cameron, and Grissmer (2018), they found that although executive functions and VMI were both related to measures of Geometry, only VMI predicted improvement in Geometry scores. They suggested that this could be due to the spatial reasoning factor of VMI (Duran et al., 2018).

In keeping with VMI as, at least in part, an indicator of cognitive ability, we found IQ to be a significant moderator of the relation between VMI and mathematics achievement but not reading achievement. Further, our results found that the relation between VMI and mathematics achievement was higher for lower-IQ students than average and higher-IQ students. This coincides with our finding that students with mental disabilities also have a higher correlation between VMI and mathematics achievement than typical children and children with physical or learning disabilities. Balsamo (2016) found a similar pattern and suggested that "children with higher IQ may have the benefit to be able to compensate for their deficits in lower order skills." (pg. 324). Meaning, having a high IQ may play a compensatory role for children with poor VMI skills which may serve as an explanation for the weaker relationship between VMI and mathematics in children with high IQs. It is also possible that students with low IQs or with mental disabilities have broad deficits across many areas, which would result in higher correlations among all cognitive measures whether or not having a higher IQ resulted in some type of compensatory ability.

The latter is also consistent with Spearman's Law of Diminishing Returns or the cognitive ability differentiation hypothesis in which correlations between cognitive abilities decrease in magnitude as IQ increases (Spearman, 1927). A recent meta-analysis on Spearman's Law of Diminishing Returns has confirmed that mean correlations among cognitive measures do tend to decrease with increasing intelligence (Blum & Holling, 2017). One reason for the diminishing returns is that children often have varied interests from one another and thus spend more time in activities that would promote skill development in some areas (e.g., reading comprehension) than others (e.g., mathematics). Highly-intelligent students learn more quickly than other students and often show larger differences across domains (e.g., literary knowledge vs. mathematical knowledge) based on where they have invested the most learning time (Blum & Holling, 2017). Less intelligent students learn more slowly and thus any gaps in knowledge between one domain (e.g., literary) or another (e.g., mathematics) emerge at a slower pace than that found in more intelligent students and one result is the gap tends to be smaller. Research also showed that fluid IQ tends to be slightly more correlated with mathematics than reading, especially for broad math measures (Peng et al., 2019). If this is the case, then the higher correlation between VMI and mathematics outcomes among students with lower IQs might simply be part of this broader pattern.

5.2. VMI as a potential measure of executive functions and attentional control

An alternative explanation for the correlation between VMI and achievement is that VMI measures and academic measures all engage executive functions and require attentional control. There is substantial evidence that executive functions relate to both visuomotor integration and academic achievement (Becker et al., 2014; Blair & Razza, 2007; Bull, Espy, & Wiebe, 2008; Cameron et al., 2015; Clark, Pritchard, & Woodward, 2010; Geary & vanMarle, 2018; Kim et al., 2016), as well as performance in a variety of other domains (Burgoyne & Engle, 2020; Kane & Engle, 2002). Executive functions are defined as higher-order cognitive processes that support planning, problem solving, and goal pursuit (Blair & Razza, 2007). The three components that constitute executive functions are working memory (i.e., ability to hold one thing in mind while engaged in another activity), cognitive flexibility (i.e., the ability to switch between tasks to meet a goal), and inhibitory control (Miyake et al., 2000). The relationship between VMI and executive functions is intuitive when considering the skills used in visuomotor integration that are dependent on EF, such as integrating attention and inhibitory control when examining an image and copying it. Additionally, it is postulated that the motor planning component of VMI relies on the working memory component of executive functions (Memisevic & Sinanovic, 2012).

The idea that attentional control and factors of executive functions could be driving a correlation between VMI and academic achievement may be supported by evidence that children's cognitive processes "specialize" as they develop (Johnson, 2001). Neuroimaging studies reveal more widespread and bilateral brain activations when a child is first learning how to read and solve arithmetic problems, whereas once a child becomes more fluent with reading or solving problems, brain activation becomes more lateralized and localized (Papanicolaou, 2003; Qin et al., 2014; Rivera, Reiss, Eckert, & Menon, 2005). It has been posited that this localization is due to the shift from relying less on executive functions for performing the academic task and more on memory retrieval as the students gains expertise in the area (Qin et al., 2014). Although neuroimaging studies investigating the development of VMI are lacking, there is evidence that VMI also requires more engagement of executive functions during the early stages of learning (Maurer & Roebers, 2021). In fact, the first stage of motor learning has been coined as the "cognitive stage" since it relies heavily on the executive functions of motor movements (Doyon, Penhune, & Ungerleider, 2003; Fitts, 1964). Thus, it is reasonable to consider executive functions as contributing to the relation between the VMI and academic achievement and may even explain our finding of stronger correlations during early childhood than during elementary school. Some researchers suggested that in early childhood, children who developed VMI early may have more attentional bandwidth to use their cognitive resources (e.g., executive functions) to learn other academic skills (Cameron, 2015; Campos et al., 2000). However, this might not explain the high correlations found between VMI and mathematics for secondary students. The continual introduction of new mathematics material during schooling means that executive functions will likely continue to influence individual differences in mathematics achievement, but its contribution to VMI performance in older students is less certain.

Despite the clear relations between VMI and executive functions, there is some evidence that VMI remains a significant predictor of mathematics achievement after controlling for executive functions (Becker et al., 2014; Duran et al., 2018; Verdine et al., 2014). There is also evidence that VMI remains a significant predictor of reading achievement after controlling for executive functions (Becker et al., 2014; Cameron et al., 2015; Sulik, Haft, & Obradović, 2018). Further, there is some evidence that executive functions and VMI can compensate for deficits in the other (Cameron et al., 2015). Meaning, if a child was found to have both poor VMI and executive functions skills, they performed worse on several achievement measures than children who were proficient in at least one of them, but the consistency of any such compensatory effects has not yet been established (Duran et al., 2018). Due to the lack of reporting of mean executive functions scores across samples, we were unable to determine the extent to which executive functions mediated the relationship between VMI and achievement. Although VMI has been found to be a unique predictor of academic achievement after controlling for executive functions, the relationship between educational stage, executive functions, VMI, and academic achievement is in need of further research.

5.3. Limitations, educational implications, and future directions

The results from this study support the use of VMI as a measure for school readiness. It may be especially useful for predicting academic readiness for early learners and children with below average IQs. Given the consistent relation between VMI and academic outcomes across development, children with visuomotor dysfunction may be at risk for further educational difficulties that extend beyond obvious visuomotor academic activities, such as handwriting.

These correlations, however, do not mean there is a causal relation between visuomotor difficulties and academic learning, as both might result from a third factor, such as executive functions. Unfortunately, there were not enough studies to assess this possibility. The risk for publication bias found for mathematics should also be considered when interpreting these results. Although trim and fill procedures did not produce notable differences in effect size, there are limitations to these procedures. For example, Shi et al. (2019) tested the use of trim-and-fill procedures on a set of Cochrane meta-analyses and found errors on estimating the number of missing studies in about 20% of the meta-analyses. . In any case, the findings illustrate that further research into the developmental and neural mechanisms associated with visuomotor integration and academic achievement could be fruitful.

One limitation of the moderation tests is that they are underpowered, so they should be interpreted with caution, particularly for those with statistically insignificant results. Lack of power means that the moderation tests are not adequately sensitive to detect all the meaningful subgroup differences or interaction effects. This is due to the limited number of studies in some categories, which increase the standard errors, as well as the fact that detecting moderation effects is more difficult than detecting main effects. Our use of multilevel meta-analyses could potentially increase power, but 80% power for moderation tests in meta-analyses is uncommon (Hempel et al., 2013). Despite this drawback, we did detect several significant moderation effects (e.g., educational stage, disability status, and IQ moderated the relationship between mathematics and VMI; and educational stage and reading category moderated the relationship between reading and VMI which provides strong evidence of those subgroup differences. However, for the insignificant results, interpreting them as the "lack of difference" should be avoided, and more empirical studies are needed for future meta-analyses to detect all meaningful moderation effects with confidence.

One particular focus for future studies is the strong relation between VMI and mathematical achievement in the secondary education stage. One explanation is that this may be related to the new content and more advanced mathematical thinking and problem-solving practices that are introduced in secondary education, such as algebraic and proportional thinking, that is dependent on attentional control and executive functions. However, only 11 reports focused on learning in middle school and high school were identified among the 102 articles which resulted in a limited understanding of this relation. Another possibility is that the relation between VMI and mathematics in later years reflects a more general trend for visuospatial skills to predict math outcomes. Compared to studies of VMI, more is known about the t relations between visuospatial skills and mathematical achievement (e.g., Hawes & Ansari, 2020; Mix, 2019). Follow-up studies are needed to determine if the relation between VMI and later mathematics achievement is mediated by more general visuospatial abilities or if there is a unique relation between VMI and later mathematics.

Experimental studies have shown that VMI can be improved through appropriate interventions (e.g., Cho, Kim, & Yang, 2015; Howe, Roston, Sheu, & Hinojosa, 2013; Ohl et al., 2013; Tzuriel & Eiboshitz, 1992). These interventions focus on different components or representative tasks of VMI, such as visual perception, bilateral coordination, and/or handwriting. Most of these interventions target early learners in special education programs. One area that is worthy to explore in the future research is the effects of the embodied engagement, defined as "purposeful body positions and movements that an individual engages in during a learning activity" (DeSutter & Stieff, 2017, p. 8), and maker-centered learning activities on students' VMI development, given the large educational investment in these initiatives recently. This meta-analysis summarized the correlations between VMI and academic achievement, and further studies can further investigate the causal relations between VMI development and academic achievement with innovative and novel instructional approaches and learning activity designs.

Author statement

Lora Khatib: Methodology, Formal analysis, Investigation, Writing – original draft preparation, Writing - Review & Editing.
Yaoran Li: Conceptualization, Investigation, Supervision, Writing – original draft preparation, Writing - Review & Editing.
David Geary: Conceptualization, Writing – original draft preparation, Writing - Review & Editing.
Vitaliy Popov: Writing – original draft preparation, Writing - Review & Editing.

Funding

This work was supported by the National Science Foundation (#1920821).

Appendix. Table of Mathematics and Reading Effect Sizes, Educational Stage, and Disability Status

Paper	N	Math Effect Size (*r*)	Reading Effect Size (*r*)	Educational Stage	Disability Status	Mean IQ of sample
Aiello-Cloutier (1993)	54	0.09	0.19	Mixed	Learning	97.3
Aiello-Cloutier (1996)	27	0.39	0.35	Secondary	Learning	96.4
Badian (1999)	1,075	0.41	0.39	Early	Learning	102.1
Balsamo et al (2016)	256	0.43	0.22	Secondary	Physical	100
Barnhardt, Borsting, Deland, Pham, and Vu (2005)	37	0.37	0.21	Mixed	Typical	103.6
Battle and Labercane (1982)	124	0.40	0.36	Mixed	Learning	97.07
Becker et al (2014)	127	0.59	0.62	Early	Typical	
Becker et al (2014)	127		0.46	Early	Typical	
Bellocchi et al (2017)	36		0.46	Early	Typical	
Bellocchi et al (2017)	36		0.19	Early	Typical	
Bellocchi et al (2017)	36		0.30	Early	Typical	
Brock, Kim, and Grissmer (2018)	259	0.17	0.18	Early	Typical	
Bruininks and Mayer (1979)	58	0.35	0.70	Secondary	Typical	105
Cameron et al (2015)	467		0.22	Early	Typical	
Cameron et al (2015)	467		0.16	Early	Typical	
Cameron et al (2015)	467		0.33	Early	Typical	

(continued on next page)

(*continued*)

Paper	N	Math Effect Size (*r*)	Reading Effect Size (*r*)	Educational Stage	Disability Status	Mean IQ of sample
Cannoni, Di Norcia, Bombi, and Di Giunta (2015)	164	0.13		Elementary	Typical	
Carlson et al (2013)	97	0.17	0.21	Mixed	Typical	107.2
Çayir (2017)	80		0.45	Elementary	Typical	
Çayir (2017)	80		0.47	Elementary	Typical	
Çayir (2017)	80		0.42	Elementary	Typical	
Chang and Chang (1967)	23		0.46	Elementary	Typical	128
Chang and Chang (1967)	27		0.39	Elementary	Typical	130
Chang and Chang (1967)	24		0.32	Elementary	Typical	128
Chang and Chang (1967)	26		0.29	Elementary	Typical	130
Chung, Lam, and Cheung (2018)	369		0.30	Early	Typical	
Colarusso, Gill, Plankenhorn, and Brooks (1980)	40	0.01	0.36	Early	Typical	
Colarusso et al. (1980)	40		0.15	Early	Typical	
Coy (1974)	51	0.11	0.05	Elementary	Typical	
De Waal, Pienaar, and Coetzee (2018)	174	0.18		Elementary	Typical	
De Waal et al. (2018)	47	0.01		Elementary	Physical	
Dere (2019)	80		0.82	Early	Typical	
Dere (2019)	80		0.47	Early	Typical	
Duffy, Clair, Egeland, and Dinello (1972)	64	0.30	0.37	Elementary	Typical	
Duffy et al. (1972)	64		0.32	Elementary	Typical	
Duffy et al. (1972)	67	0.39	0.45	Elementary	Typical	
Duffy et al. (1972)	67		0.51	Elementary	Typical	
Duffy et al. (1972)	57	0.41	0.43	Elementary	Typical	
Duffy et al. (1972)	57		0.46	Elementary	Typical	
Dunn, Loxton, and Naidoo (2006)	238	0.44	0.42	Early	Typical	
Dunn et al. (2006)	238	0.58	0.60	Early	Typical	
Duran et al (2018)	89	0.50		Early	Typical	
De Waal et al. (2018)	89	0.53		Early	Typical	
De Waal et al. (2018)	89	0.48		Early	Typical	
De Waal et al. (2018)	89	0.40		Early	Typical	
De Waal et al. (2018)	89	0.47		Early	Typical	
De Waal et al. (2018)	89	0.53		Early	Typical	
De Waal et al. (2018)	73	0.56		Elementary	Typical	
De Waal et al. (2018)	73	0.57		Elementary	Typical	
De Waal et al. (2018)	73	0.55		Elementary	Typical	
De Waal et al. (2018)	73	0.53		Elementary	Typical	
De Waal et al. (2018)	73	0.51		Elementary	Typical	
De Waal et al. (2018)	73	0.61		Elementary	Typical	
Farmer (1998)	174	0.34	0.33	Early	Typical	
Farmer (1998)	124	0.31	0.26	Early	Typical	
Farmer (1998)	117	0.25	0.23	Early	Typical	
Farmer (1998)	92	0.31	0.16	Secondary	Typical	
Feshbach, Adelman, and Fuller (1977)	403		0.24	Elementary	Typical	
Feshbach et al. (1977)	403		0.25	Elementary	Typical	
Feshbach et al. (1977)	403		0.24	Elementary	Typical	
Fletcher-Flinn, Elmers, and Struynell (1997)	28		0.11	Elementary	Physical	99.4
Miller (1986)	338	0.38	0.40	Elementary	Typical	115.1
Fowler and Cross (1986)	176	0.22	0.17	Mixed	Typical	
French (2003)	227	0.62	0.50	Mixed	Mental	
French (2003)	227	0.35	0.30	Mixed	Mental	
Fuller and Friedrich (1973)	203		0.29	Secondary	Typical	97.03
Fuller and Wallbrown (1983)	69	0.27	0.26	Elementary	Typical	108.6
Gebhardt (2004)	64		0.57	Early	Typical	
Gebhardt (2004)	58		0.53	Elementary	Typical	
Gebhardt (2004)	58		0.44	Elementary	Typical	
Gebhardt (2004)	63		0.04	Elementary	Typical	
Gebhardt (2004)	51		0.18	Elementary	Typical	
Geertsen et al. (2016)	423	0.20	0.26	Elementary	Typical	
Geis (1971)	242		0.87	Early	Typical	101.5
Glidden (2000)	66	0.15	0.13	Mixed	Learning	102
Goldstein and Britt (1994)	44	0.62	0.54	Mixed	Mental	84.9
Goldstein and Britt (1994)	44	0.65	0.47	Mixed	Mental	85.9
Greenburg, Carlson, Kim, Curby, and Winsler (2020)	16,935	0.38	0.36	Elementary	Typical	
Greenburg et al. (2020)	16,935	0.33	0.34	Elementary	Typical	
Greenburg et al. (2020)	16,935	0.29	0.29	Elementary	Typical	
Hamilton (2001)	44		0.43	Elementary	Typical	
Hanson (1969)	122		0.33	Elementary	Physical	84.3
Hasler and Akshoomoff (2019)	87	0.48		Early	Physical	106.3
Hernández Finch, Speirs Neumeister, Burney, and Cook (2014)	61	0.02	0.27	Early	Typical	131.4

(*continued on next page*)

(*continued*)

Paper	N	Math Effect Size (*r*)	Reading Effect Size (*r*)	Educational Stage	Disability Status	Mean IQ of sample
Hick (1970)	26	0.69	0.69	Elementary	Typical	
Hinshaw, Carte, and Morrison (1986)	39	0.70	0.63	Elementary	Learning	109.8
Hinshaw et al. (1986)	39		0.66	Elementary	Learning	109.8
Hopkins, Black, White, and Wood (2019)	222	0.32	0.38	Elementary	Typical	
Horn and O'Donnell (1984)	218	0.54	0.48	Elementary	Typical	
Kaemingk, Carey, Moore, Herzer, and Hutter (2004)	15	0.35		Mixed	Physical	98.8
Kaemingk et al. (2004)	15	0.58		Mixed	Physical	98.8
Kaemingk et al. (2004)	15	0.60		Mixed	Physical	98.8
Kaemingk et al. (2004)	15	0.64		Mixed	Physical	98.8
Kaemingk et al. (2004)	15	0.61		Mixed	Physical	98.8
Kaemingk et al. (2004)	15	0.73		Mixed	Typical	113.8
Kaemingk et al. (2004)	15	0.47		Mixed	Typical	113.8
Kaemingk et al. (2004)	15	0.79		Mixed	Typical	113.8
Kaemingk et al. (2004)	15	0.62		Mixed	Typical	113.8
Kaemingk et al. (2004)	15	0.65		Mixed	Typical	113.8
Karlsdottir and Stefansson (2003)	407		0.32	Elementary	Typical	
Karlsdottir and Stefansson (2003)	407		0.26	Elementary	Typical	
Kastner, May, and Hildman (2001)	280		0.31	Early	Typical	
Kim et al (2018)	249	0.57		Early	Typical	
Kim et al (2018)	240	0.59		Elementary	Typical	
Kim et al (2018)	166	0.67		Elementary	Typical	
Klein (1978)	679	0.50	0.41	Elementary	Typical	
Klein (1978)	679	0.41	0.27	Elementary	Typical	
Klein (1978)	679	0.34	0.35	Elementary	Typical	
Klein (1978)	766	0.44	0.42	Elementary	Typical	
Klein (1978)	766		0.39	Elementary	Typical	
Kurdek and Sinclair (2001)	281	0.21	0.08	Secondary	Typical	
Lachance and Mazzocco (2006)	249	0.49		Early	Typical	
Lachance and Mazzocco (2006)	236	0.43		Elementary	Typical	
Lachance and Mazzocco (2006)	224	0.37		Elementary	Typical	
Lachance and Mazzocco (2006)	214	0.36		Elementary	Typical	
Leton (1962)	23	0.41	0.41	Elementary	Mental	
Leton (1962)	23	0.37	0.36	Elementary	Mental	
Lindgren (1978)	100	0.52	0.37	Early	Typical	115.6
Lindgren (1978)	100		0.28	Early	Typical	115.6
Lindgren (1978)	100		0.33	Early	Typical	115.6
Majsterek and Lord (1991)	84		0.14	Early	Typical	96.4
Majsterek and Lord (1991)	84		0.14	Early	Typical	96.4
Mati-Zissi and Zafiropoulou (2003)	204		0.09	Elementary	Learning	
Mati-Zissi and Zafiropoulou (2003)	204		0.10	Elementary	Learning	
Mati-Zissi and Zafiropoulou (2003)	204		0.07	Elementary	Learning	
Mayes, Calhoun, Bixler, and Vgontzas (2008)	412	0.44	0.41	Elementary	Typical	
Memiş and Sivri (2016)	168		0.45	Elementary	Typical	
Memiş and Sivri (2016)	168		0.47	Elementary	Typical	
Memiş and Sivri (2016)	168		0.42	Elementary	Typical	
Memisevic, Biscevic, and Pasalic (2018)	210	0.50		Elementary	Typical	
Memisevic et al (2019)	140		0.17	Elementary	Typical	
Meng, Wydell, and Bi (2019)	61		0.26	Elementary	Learning	
Moore et al. (2016)	71	0.43	0.48	Early	Physical	
Moore et al. (2016)	71	0.36	0.58	Early	Physical	
Moore et al. (2016)	71	0.48	0.56	Early	Physical	
Moore et al. (2016)	71	0.47	0.46	Early	Physical	
Morgenstern and McIvor (1973)	76	0.42	0.20	Secondary	Mental	61.27
Nesbitt, Fuhs, and Farran (2019)	1,138	0.29		Early	Typical	
Nesbitt et al. (2019)	1,138	0.22		Early	Typical	
Nesbitt et al. (2019)	1,138	0.19		Early	Typical	
Nesbitt et al. (2019)	1,138	0.23		Elementary	Typical	
Newton (1966)	172		0.45	Elementary	Typical	99.93
Nielson and Sapp (1991)	72	0.38	0.25	Elementary	Physical	89.1
Nielson and Sapp (1991)	81	0.16	0.16	Elementary	Typical	99.9
Oberer, Gashaj, and Roebers (2018)	134	0.38	0.20	Early	Typical	
Oberer et al. (2018)	134	0.30	0.24	Early	Typical	
Oliver (2013)	45	0.74	0.45	Mixed	Mental	104.4
Oliver (2013)	45		0.57	Mixed	Mental	104.4
Pienaar (2019)	816	0.38	0.36	Elementary	Physical	
Pieters, Desoete, Roeyers, Vanderswalmen, and Van Waelvelde (2012)	145	0.33		Elementary	Learning	
Pieters, Roeyers, Rosseel, Van Waelvelde, and Desoete (2015)	410	0.30		Elementary	Physical	95

(*continued on next page*)

(*continued*)

Paper	N	Math Effect Size (*r*)	Reading Effect Size (*r*)	Educational Stage	Disability Status	Mean IQ of sample
Pieters et al. (2015)	410	0.24		Elementary	Physical	98.7
Pitchford, Papini, Outhwaite, and Gulliford (2016)	62	0.57	0.38	Early	Typical	
Preda (1997)	60	0.39		Elementary	Typical	
Richardson, DiBenedetto, Christ, and Press (1980)	77	0.22		Elementary	Learning	82.21
Richardson et al. (1980)	77	0.22		Elementary	Learning	82.21
Richardson et al. (1980)	77	0.20		Elementary	Learning	82.21
Roberts, Bellinger, and McCormick (2007)	469	0.66		Early	Physical	88.9
Roberts et al. (2007)	494		0.70	Early	Physical	88.9
Sandoval and Hughes (1981)	146	0.07	0.03	Elementary	Typical	
Santi et al (2015)	778		0.33	Elementary	Typical	111.6
Santi et al (2015)	778		0.19	Elementary	Typical	111.6
Santi et al (2015)	778		0.21	Elementary	Typical	111.6
Sapp (1984)	32	0.38		Elementary	Mental	99
Sewell (2008)	75	0.64		Secondary	Typical	
Sewell (2008)	75	0.60		Secondary	Typical	
Sewell (2008)	75	0.47		Secondary	Typical	
Sewell (2008)	75	0.64		Secondary	Typical	
Sewell (2008)	75	0.63		Secondary	Typical	
Sewell (2008)	75	0.63		Secondary	Typical	
Shepherd (1969)	47	0.60	0.40	Elementary	Physical	98.23
Simms, Clayton, Cragg, Gilmore, and Johnson (2016)	77	0.48		Elementary	Typical	
Son and Meisels (2006)	12,583	0.44	0.35	Early	Typical	
Son and Meisels (2006)	12,583	0.48	0.40	Elementary	Typical	
Sortor and KULP (2003)	155	0.27	0.16	Secondary	Typical	
Sulik et al (2018)	343	0.31	0.40	Elementary	Typical	
Sulik et al (2018)	343	0.37	0.34	Elementary	Typical	
Sullivan and McGrath (2003)	168	0.42	0.32	Elementary	Physical	
Taha (2016)	50	0.85		Secondary	Mental	59.91
Taylor (1999)	191	0.36	0.38	Mixed	Typical	
Tillman (1974)	60		0.26	Elementary	Typical	107
Tillman (1974)	60		0.32	Elementary	Typical	107
Tillman (1974)	60		0.26	Elementary	Typical	107
Verdine et al (2014)	44	0.67		Early	Typical	
Wallbrown, Engin, Wallbrown, and Blaha (1975)	100		0.49	Early	Typical	104.1
Wallbrown, Wallbrown, and Engin (1977)	153	0.26	0.27	Elementary	Typical	116.9
Wallbrown et al. (1977)	153	0.18	0.24	Elementary	Typical	116.9
Webb (1985)	30	0.65	0.55	Secondary	Mental	64.2
Webb and Abe (1984)	28	0.67	0.42	Secondary	Mental	61.3
Welcher, Wessel, Mellits, and Hardy (1974)	202	0.25	0.32	Early	Typical	91
Wright (1976)	70		0.36	Elementary	Typical	
Wright (1976)	70		0.37	Elementary	Typical	
Wright (1976)	70		0.40	Elementary	Typical	

References

Abrahamson, D., & Sánchez-García, R. (2016). Learning is moving in new ways: The ecological dynamics of mathematics education. *Journal of the Learning Sciences, 25*(2), 203–239.

Alibali, M. W., & Nathan, M. J. (2012). Embodiment in mathematics teaching and learning: Evidence from learners' and teachers' gestures. *Journal of the Learning Sciences, 21*(2), 247–286.

Andres, M., Ostry, D. J., Nicol, F., & Paus, T. (2008). Time course of number magnitude interference during grasping. *Cortex, 44*(4), 414–419.

Balsamo, L. M., Sint, K. J., Neglia, J. P., Brouwers, P., & Kadan-Lottick, N. S. (2016). The association between motor skills and academic achievement among pediatric survivors of acute lymphoblastic leukemia. *Journal of Pediatric Psychology, 41*(3), 319–328.

Becker, D. R., Miao, A., Duncan, R., & McClelland, M. M. (2014). Behavioral self-regulation and executive function both predict visuomotor skills and early academic achievement. *Early Childhood Research Quarterly, 29*(4), 411–424.

Beery, K. E. (1989). *Developmental test of visual-motor integration: Administration, scoring and teaching manual*. Modern Curriculum Press.

Beery, K. E., & Beery, N. A. (2006). *The developmental test of visual motor integration*. Minneapolis: NCS Pearson Inc.

Beery, K. E., Buktenica, N. A., & Beery, N. A. (1997). *The Beery-Buktenica developmental test of visual-motor integration: VMI, with supplemental developmental tests of visual perception and motor coordination: Administration, scoring and teaching manual*. Modern Curriculum Press.

Bellocchi, S., Muneaux, M., Huau, A., Lévêque, Y., Jover, M., & Ducrot, S. (2017). Exploring the link between visual perception, visual–motor integration, and reading in normal developing and impaired children using DTVP-2. *Dyslexia, 23*(3), 296–315.

Bender, L. (1938). *A visual motor gestalt test and its clinical use*. American Orthopsychiatric Association. Research Monographs.

Berch, D. B., Geary, D. C., & Koepke, K. M. (Eds.). (2015). *Development of mathematical cognition: Neural substrates and genetic influences*. Academic Press.

Blair, C., & Razza, R. P. (2007). Relating effortful control, executive function, and false belief understanding to emerging math and literacy ability in kindergarten. *Child Development, 78*(2), 647–663.

Blum, D., & Holling, H. (2017). Spearman's law of diminishing returns. A meta-analysis. *Intelligence, 65*, 60–66.

Borenstein, M., Hedges, L. V., Higgins, J. P., & Rothstein, H. R. (2011). *Introduction to meta-analysis*. John Wiley & Sons.

Brissiaud, R. (2011). *Comment les enfants apprennent à calculer*. Retz.

Bull, R., Espy, K. A., & Wiebe, S. A. (2008). Short-term memory, working memory, and executive functions in preschoolers: Longitudinal predictors of mathematical achievement at age 7 years. *Developmental Neuropsychology, 33*, 205–228.
Bull, R., & Lee, K. (2014). Executive functioning and mathematics achievement. *Child Development Perspectives, 8*, 36–41. https://doi.org/10.1111/cdep.12059
Bullock, D., Grossberg, S., & Guenther, F. H. (1993). A self-organizing neural model of motor equivalent reaching and tool use by a multijoint arm. *Journal of Cognitive Neuroscience, 5*(4), 408–435.
Burgoyne, A. P., & Engle, R. W. (2020). Attention control: A cornerstone of higher-order cognition. *Current Directions in Psychological Science, 29*, 624–630.
Cameron, C. E., Brock, L. L., Hatfield, B. E., Cottone, E. A., Rubinstein, E., LoCasale-Crouch, J., et al. (2015). Visuomotor integration and inhibitory control compensate for each other in school readiness. *Developmental Psychology, 51*(11), 1529.
Campos, J. J., Anderson, D. I., Barbu-Roth, M. A., Hubbard, E. M., Hertenstein, M. J., & Witherington, D. (2000). Travel broadens the mind. *Infancy, 1*(2), 149–219. https://doi.org/10.1207/S15327078IN0102_1
Carbonneau, K. J., Marley, S. C., & Selig, J. P. (2013). A meta-analysis of the efficacy of teaching mathematics with concrete manipulatives. *Journal of Educational Psychology, 105*(2), 380.
Carlson, A. G., Rowe, E., & Curby, T. W. (2013). Disentangling fine motor skills' relations to academic achievement: The relative contributions of visual-spatial integration and visual-motor coordination. *The Journal of Genetic Psychology, 174*(5), 514–533.
Cho, M., Kim, D., & Yang, Y. (2015). Effects of visual perceptual intervention on visual-motor integration and activities of daily living performance of children with cerebral palsy. *Journal of Physical Therapy Science, 27*(2), 411–413.
Chu, F. W., vanMarle, K., Rouder, J., & Geary, D. C. (2018). Children's early understanding of number predicts their later problem-solving sophistication in addition. Journal of. *Experimental Child Psychology, 169*, 73–92.
Clark, C. A. C., Pritchard, V. E., & Woodward, L. J. (2010). Preschool executive functioning abilities predict early mathematics achievement. *Developmental Psychology, 46*, 1176–1191.
Cohen, J. (1992). A power primer. *Psychological Bulletin, 112*(1), 155.
Cooperrider, K., Gentner, D., & Goldin-Meadow, S. (2016). Spatial analogies pervade complex relational reasoning: Evidence from spontaneous gestures. *Cognitive Research: Principles and Implications, 1*(1), 28.
Dawson, G., & Watling, R. (2000). Interventions to facilitate auditory, visual, and motor integration in autism: A review of the evidence. *Journal of Autism and Developmental Disorders, 30*(5), 415–421.
Deary, I. J., Strand, S., Smith, P., & Fernandes, C. (2007). Intelligence and educational achievement. *Intelligence, 35*, 13–21. https://doi.org/10.1016/j.intell.2006.02.001
DeSutter, D., & Stieff, M. (2017). Teaching students to think spatially through embodied actions: Design principles for learning environments in science, technology, engineering, and mathematics. *Cognitive Research: Principles and Implications, 2*(1), 1–20.
Doyon, J., Penhune, V., & Ungerleider, L. G. (2003). Distinct contribution of the cortico-striatal and cortico-cerebellar systems to motor skill learning. *Neuropsychologia, 41*(3), 252–262.
Duran, C. A., Byers, A., Cameron, C. E., & Grissmer, D. (2018). Unique and compensatory associations of executive functioning and visuomotor integration with mathematics performance in early elementary school. *Early Childhood Research Quarterly, 42*, 21–30.
Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *Bmj, 315*(7109), 629–634.
Fischer, M. H. (2008). Finger counting habits modulate spatial-numerical associations. *Cortex, 44*(4), 386–392.
Fitts, P. M. (1964). Perceptual-motor skill learning. In *Categories of human learning* (pp. 243–285). Academic Press.
Franceschini, S., Gori, S., Ruffino, M., Pedrolli, K., & Facoetti, A. (2012). A causal link between visual spatial attention and reading acquisition. *Current Biology, 22*(9), 814–819.
Fuson, K. C. (1988). *Children's counting and concepts of number*. New York: Springer-Verlag. https://doi: 10.1007/978-1-4612-3754-9.
Geary, D. C., & Burlingham-Dubree, M. (1989). External validation of the strategy choice model for addition. *Journal of Experimental Child Psychology, 47*(2), 175–192.
Geary, D. C., Hoard, M. K., Nugent, L., Ünal, Z. E., & Scofield, J. E. (2020). Comorbid learning difficulties in reading and mathematics: The role of intelligence and in-class attentive behavior. *Frontiers in Psychology, 11*, 572099. https://doi.org/10.3389/fpsyg.2020.572099
Geary, D. C., & vanMarle, K. (2018). Growth of symbolic number knowledge accelerates after children understand cardinality. *Cognition, 177*, 69–78.
Geary, D. C., vanMarle, K., Chu, F., Rouder, J., Hoard, M. K., & Nugent, L. (2018). Early conceptual understanding of cardinality predicts superior school-entry number system knowledge. *Psychological Science, 29*, 191–205.
Gelman, R., & Gallistel, C. R. (1978). *The child's understanding of number*. Cambridge, Mass: Harvard University Press. https://doi: 10.2307/1175067.
Gerstmann, J. (1940). Syndrome of finger agnosia, disorientation for right and left, agraphia and acalculia: Local diagnostic value. *Archives of Neurology & Psychiatry, 44*(2), 398–408.
Goldstein, D. J., & Britt, T. W., Jr. (1994). Visual-motor coordination and intelligence as predictors of reading, mathematics, and written language ability. *Perceptual and Motor Skills, 78*(3), 819–823.
Guarino, C., Dieterle, S. G., Bargagliotti, A. E., & Mason, W. M. (2013). What can we learn about effective early mathematics teaching? A framework for estimating causal effects using longitudinal survey data. *Journal of Research on Educational Effectiveness, 6*(2), 164–198.
Guigon, E., & Baraduc, P. (2002). A neural model of perceptual-motor alignment. Journal of. *Cognitive Neuroscience, 14*(4), 538–549.
Hammill, D. D. (2004). What we know about correlates of reading. *Exceptional Children, 70*(4), 453–469.
Harrer, M., Cuijpers, P., Furukawa, T. A., & Ebert, D. D. (2019). *Doing meta-analysis in R: A hands-on guide*. PROTECT Lab Erlangen.
Hawes, Z., & Ansari, D. (2020). What explains the relationship between spatial and mathematical skills? A review of evidence from the brain and behavior. *Psychonomic Bulletin & Review, 27*, 465–482. https://doi.org/10.3758/s13423-019-01694-7
Hempel, S., Miles, J. N., Booth, M. J., Wang, Z., Morton, S. C., & Shekelle, P. G. (2013). Risk of bias: A simulation study of power to detect study-level moderator effects in meta-analysis. *Systematic Reviews, 2*(1), 1–10.
Henry, L. A., Bettenay, C., & Carney, D. (2011). Children with intellectual disabilities and developmental disorders. In *Children's testimony: A handbook of psychological research and forensic practice* (2nd ed., pp. 251–283). https://doi.org/10.1002/9781119998495. Ch13
Henschen, S. E., & Schaller, W. F. (1925). Clinical and anatomical contributions on brain pathology. *Archives of Neurology & Psychiatry, 13*, 226–249.
Howe, T. H., Roston, K. L., Sheu, C. F., & Hinojosa, J. (2013). Assessing handwriting intervention effectiveness in elementary school students: A two-group controlled study. *American Journal of Occupational Therapy, 67*(1), 19–26.
Iversen, S., Berg, K., Ellertsen, B., & Tonnessen, F. E. (2005). Motor coordination difficulties in a municipality group and in a clinical sample of poor readers. *Dyslexia, 11*(3), 217–231.
Jarvis, H. L., & Gathercole, S. E. (2003). Verbal and nonverbal working memory and achievements on national curriculum tests at 7 and 14 years of age. *Educational and Child Psychology, 20*, 123140.
Jastak, S., & Wilkinson, G. S. (1984). *The wide range achievement test-revised*. Jastak Associates.
Johnson, M. H. (2001). Functional brain development in humans. *Nature Reviews Neuroscience, 2*(7), 475–483.
Kane, M. J., & Engle, R. W. (2002). The role of prefrontal cortex in working-memory capacity, executive attention, and general fluid intelligence: An individual-differences perspective. *Psychonomic Bulletin & Review, 9*, 637–671.
Kim, H., Byers, A. I., Cameron, C. E., Brock, L. L., Cottone, E. A., & Grissmer, D. W. (2016). *Attentional control and visuomotor integration uniquely contribute to children's successful classroom functioning*. Center for Advanced Study of Teaching and Learning Research Brief.
Kim, H., Duran, C. A., Cameron, C. E., & Grissmer, D. (2018). Developmental relations among motor and cognitive processes and mathematics skills. *Child Development, 89*(2), 476–494.
Kredlow, M. A., Unger, L. D., & Otto, M. W. (2016). Harnessing reconsolidation to weaken fear and appetitive memories: A meta-analysis of post-retrieval extinction effects. *Psychological Bulletin, 142*(3), 314.
Lee, K., & Bull, R. (2016). Developmental changes in working memory, updating, and math achievement. *Journal of Educational Psychology, 108*(6), 869.

Li, Y., & Geary, D. C. (2013). Developmental gains in visuospatial memory predict gains in mathematics achievement. *PLoS One, 8*(7), Article e70160.
Li, Y., & Geary, D. C. (2017). Children's visuospatial memory predicts mathematics achievement through early adolescence. *PLoS One, 12*(2), Article e0172046.
Longcamp, M., Richards, T. L., Velay, J. L., & Berninger, V. W. (2016). Neuroanatomy of handwriting and related reading and writing skills in adults and children with and without learning disabilities: French-american connections. *Pratiques*, 171–172. https://doi.org/10.4000/pratiques.3175
Longcamp, M., Zerbato-Poudou, M. T., & Velay, J. L. (2005). The influence of writing practice on letter recognition in preschool children: A comparison between handwriting and typing. *Acta Psychologica, 119*(1), 67–79.
MacGinitie, W. H. (1978). *Gates-MacGinitie reading tests*. Boston: Houghton Mifflin.
Maurer, M. N., & Roebers, C. M. (2021). New insights into visual-motor integration exploring process measures during copying shapes. *Psychology of Sport and Exercise, 55*, 101954.
Maybery, M. T., & Do, N. (2003). Relationships between facets of working memory and performance on a curriculum-based mathematics test in children. *Educational and Child Psychology, 20*, 7792.
McCoach, D. B., Yu, H., Gottfried, A. W., & Gottfried, A. E. (2017). Developing talents: A longitudinal examination of intellectual ability and academic achievement. *High Ability Studies, 28*(1), 7–28.
Medwell, J., & Wray, D. (2014). Handwriting automaticity: The search for performance thresholds. *Language and Education, 28*(1), 34–51.
Memisevic, H., Malec, D., & Biscevic, I. (2019). Predictors of reading fluency in second and third grade students: Results from Bosnia and Herzegovina. *Studia Psychologica, 61*(3), 175–188.
Memisevic, H., & Sinanovic, O. (2012). Predictors of visual-motor integration in children with intellectual disability. *International Journal of Rehabilitation Research, 35*(4), 372–374.
Miller, L. J. (1986). *The Miller Assessment for Preschoolers: A longitudinal and predictive study final report*. No. 190 (p. 996). Report.
Mix, K. S. (2019). Why are spatial skill and mathematics related? *Child Development Perspectives, 13*, 121–126. https://doi: 10.1111/cdep12323.
Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology, 41*(1), 49–100.
Morgenstern, M., & McIvor, W. (1973). The relationship between Bender Gestalt performance and achievement among retardates. *The Training School Bulletin, 70*(2), 84–87.
Naglieri, J. A., & Ronning, M. E. (2000). Comparison of white, African American, Hispanic, and Asian children on the Naglieri nonverbal ability test. *Psychological Assessment, 12*(3), 328.
Núñez, R. (2008). A fresh look at the foundations of mathematics: Gesture and the psychological reality of conceptual metaphor. *Metaphor and Gesture, 93*, 114.
Ohl, A. M., Graze, H., Weber, K., Kenny, S., Salvatore, C., & Wagreich, S. (2013). Effectiveness of a 10-week Tier-1 Response to Intervention program in improving fine motor and visual–motor skills in general education kindergarten students. *American Journal of Occupational Therapy, 67*(5), 507–514.
Papanicolaou, A. C., Simos, P. G., Breier, J. I., Fletcher, J. M., Foorman, B. R., Francis, D., … Davis, R. N. (2003). Brain mechanisms for reading in children with and without dyslexia: A review of studies of normal development and plasticity. *Developmental Neuropsychology, 24*(2–3), 593–612.
Peng, P., Wang, T., Wang, C., & Lin, X. (2019). A meta-analysis on the relation between fluid intelligence and reading/mathematics: Effects of tasks, age, and social economics status. *Psychological Bulletin, 145*(2), 189.
Pham, A. V., & Hasson, R. M. (2014). Verbal and visuospatial working memory as predictors of children's reading ability. *Archives of Clinical Neuropsychology, 29*(5), 467–477.
Polanin, J. R. (2014). *An introduction to multilevel meta-analysis*. Belfast, UK: Campbell Collaboration. Campbell Colloquium.
Psychological Corporation. (2002). *Stanford achievement test* (10th ed.). San Antonio, TX: Harcourt Brace & Company, Educational Measurement.
Qin, S., Cho, S., Chen, T., Rosenberg-Lee, M., Geary, D. C., & Menon, V. (2014). Hippocampal- neocortical functional reorganization underlies children's cognitive development. *Nature Neuroscience, 17*, 1263–1269.
Quintana, D. S. (2015). From pre-registration to publication: A non-technical primer for conducting a meta-analysis to synthesize correlational data. *Frontiers in Psychology, 6*, 1549. https://doi.org/10.3389/fpsyg.2015.01549
Reuhkala, M. (2001). Mathematical skills in ninth-graders: Relationship with visuo-spatial abilities and working memory. *Educational Psychology, 21*, 387399.
Rivera, S. M., Reiss, A. L., Eckert, M. A., & Menon, V. (2005). Developmental changes in mental arithmetic: Evidence for increased functional specialization in the left inferior parietal cortex. *Cerebral Cortex, 15*(11), 1779–1790.
Santi, K. L., Francis, D. J., Currie, D., & Wang, Q. (2015). Visual motor integration skills: Accuracy of predicting reading. *Optometry and Vision Science, 92*(2), 217.
Shi, L., & Lin, L. (2019). The trim-and-fill method for publication bias: Practical guidelines and recommendations based on a large database of meta-analyses. *Medicine, 98*(23).
Siegler, R. S., & Robinson, M. (1982). The development of numerical understandings. In W. R. Hayne, & P. L. Lewis (Eds.), *Advances in child development and behavior, 16* pp. 241–312). https://doi.org/10.1016/S0065-2407(08)60072-5
Son, S. H., & Meisels, S. J. (2006). The relationship of young children's motor skills to later reading and math achievement. *Merrill-Palmer Quarterly*, 755–778.
Sortor, J. M., & Kulp, M. T. (2003). Are the results of the Beery-Buktenica Developmental Test of Visual-Motor Integration and its subtests related to achievement test scores? *Optometry and Vision Science, 80*(11), 758–763.
Spearman, C. (1927). The abilities of man. *Revue Philosophique de Louvain, 29*(16), 491–492.
Stieff, M., Lira, M. E., & Scopelitis, S. A. (2016). Gesture supports spatial thinking in STEM. *Cognition and Instruction, 34*(2), 80–99.
Sulik, M. J., Haft, S. L., & Obradović, J. (2018). Visual-motor integration, executive functions, and academic achievement: Concurrent and longitudinal relations in late elementary school. *Early Education and Development, 29*(7), 956–970.
Taylor, M. K. (1999). Relationship between visual motor integration skill and academic performance in kindergarten through third grade. *Optometry and Vision Science, 76*(3), 159–163.
Tiegs, E., & Clark, W. (1977). *California achievement test*. Monterey, Calif: CTB.
Tzuriel, D., & Eiboshitz, Y. (1992). Structured program of visual-motor integration (SP-VMI) for preschool children. *Learning and Individual Differences, 4*(2), 103–124.
Verdine, B. N., Irwin, C. M., Golinkoff, R. M., & Hirsh-Pasek, K. (2014). Contributions of executive function and spatial skills to preschool mathematics achievement. *Journal of Experimental Child Psychology, 126*, 37–51.
Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software, 36*(3), 1–48. https://www.jstatsoft.org/v36/i03/.
Volman, M. J. M., van Schendel, B. M., & Jongmans, M. J. (2006). Handwriting 16 difficulties in primary school children: A search for underlying 17 mechanisms. *American Journal of Occupational Therapy, 60*, 451–460.
Waterman, A. H., Havelka, J., Culmer, P. R., Hill, L. J., & Mon-Williams, M. (2015). The ontogeny of visual–motor memory and its importance in handwriting and reading: A developing construct. *Proceedings of the Royal Society B: Biological Sciences, 282*(1798), 20140896.
Wechsler, D. (2005). *Wechsler individual achievement test* (2nd ed.). London: The Psychological Corp *(WIAT II)*.
Weintraub, N., & Graham, S. (2000). The contribution of gender, orthographic, finger function, and visual-motor processes to the prediction of handwriting status. *The Occupational Therapy Journal of Research, 20*(2), 121–140.
Wei, W., Yuan, H., Chen, C., & Zhou, X. (2012). Cognitive correlates of performance in advanced mathematics. *British Journal of Educational Psychology, 82*(1), 157–181.
Woodcock, R. W. (1977). *Woodcock-johnson psycho-educational battery*. Technical Report.
Wuang, Y. P., Wang, C. C., Huang, M. H., & Su, C. Y. (2008). Profiles and cognitive predictors of motor functions among early school-age children with mild intellectual disabilities. *Journal of Intellectual Disability Research, 52*(12), 1048–1060.

References

Aiello-Cloutier, M. (1993). Visual-motor skills as a predictor of written expression. In *Washington, DC: Conference of the national association of school psychologists*. ERIC. Document Reproduction Services No. ED 375533.

Aiello-Cloutier, M. D. (1996). The developmental test of visual-motor integration and written expression: A validity investigation with middle school students who are identified as learning-disabled. Retrieved from https://www.elibrary.ru/item.asp?id=5650598.

Badian, N. A. (1999). Persistent arithmetic, reading, or arithmetic and reading disability. *Annals of Dyslexia, 49*(1), 43.

Barnhardt, C., Borsting, E., Deland, P., Pham, N., & Vu, T. (2005). Relationship between visual-motor integration and spatial organization of written language and math. *Optometry and Vision Science, 82*(2), 138–143.

Battle, J., & Labercane, G. (1982). Relationship between achievement and ability. *Psychological Reports, 50*(3), 1284–1286.

Brock, L. L., Kim, H., & Grissmer, D. W. (2018). Longitudinal associations among executive function, visuomotor integration, and achievement in a high-risk sample. *Mind, Brain, and Education, 12*(1), 23–27.

Bruininks, V. L., & Mayer, J. H. (1979). Longitudinal study of cognitive abilities and academic achievement. *Perceptual and Motor Skills, 48*(3), 1011–1021.

Cannoni, E., Di Norcia, A., Bombi, A. S., & Di Giunta, L. (2015). The bicycle drawing test: What does it measure in developmentally typical children? *Assessment, 22*(5), 629–639.

Çayir, A. (2017). Analyzing the reading skills and visual perception levels of first grade students. *Universal Journal of Educational Research, 5*(7), 1113–1116.

Chang, T. M., & Chang, V. A. (1967). Relation of visual-motor skills and reading achievement in primary-grade pupils of superior ability. *Perceptual and Motor Skills, 24*(1), 51–53.

Chung, K. K. H., Lam, C. B., & Cheung, K. C. (2018). Visuomotor integration and executive functioning are uniquely linked to Chinese word reading and writing in kindergarten children. *Reading and Writing, 31*(1), 155–171.

Colarusso, R., Gill, S., Plankenhorn, A., & Brooks, R. (1980). Predicting first-grade achievement through formal testing of 5-year-old high-risk children. *The Journal of Special Education, 14*(3), 355–363.

Coy, M. N. (1974). The bender visual-motor Gestalt test as a predictor of academic achievement. *Journal of Learning Disabilities, 7*(5), 317–319.

De Waal, E., Pienaar, A. E., & Coetzee, D. (2018). Perceptual-motor contributors to the association between developmental coordination disorder and academic performance: North-West Child Health, Integrated with Learning and Development study. *South African Journal of Childhood Education, 8*(2), 1–11.

Dere, Z. (2019). Analyzing the early literacy skills and visual motor integration levels of kindergarten students. *Journal of Education and Learning, 8*(2), 176–181.

Duffy, O. B., Clair, T. N., Egeland, B., & Dinello, M. (1972). Relationship of intelligence, visual-motor skills, and psycholinguistic abilities with achievement in the third, fourth, and fifth grades: A follow-up study. *Journal of Educational Psychology, 63*(4), 358.

Dunn, M., Loxton, H., & Naidoo, A. (2006). Correlations of scores on the developmental test of visual-motor integration and copying test in a South African multi-ethnic preschool sample. *Perceptual and Motor Skills, 103*(3), 951–958.

Farmer, K. (1998). Screening school children: Benefits and liabilities. Retrieved from https://www.elibrary.ru/item.asp?id=5553087.

Feshbach, S., Adelman, H., & Fuller, W. (1977). Prediction of reading and related academic problems. *Journal of Educational Psychology, 69*(4), 299.

Fletcher-Flinn, C., Elmers, H., & Strutnell, D. (1997). Visual-perceptual and phonological factors in the acquisition of literacy among children with congenital developmental coordination disorder. *Developmental Medicine & Child Neurology, 39*(3), 158–166.

Fowler, M. G., & Cross, A. W. (1986). Preschool risk factors as predictors of early school performance. *Journal of Developmental and Behavioral Pediatrics, 7*(4), 237–241. https://doi.org/10.1097/00004703-198608000-00004

French, C. L. (2003). *The applicability of children's drawings in predicting academic achievement and differentiating between clinical and nonclinical groups*. Doctoral dissertation. Texas A & M University.

Fuller, G., & Friedrich, D. (1973). Predicting potential school problems. *Perceptual and Motor Skills, 37*(2), 453–454.

Fuller, G. B., & Wallbrown, F. H. (1983). Comparison of the Minnesota Percepto-diagnostic test and Bender-gestalt: Relationship with achievement criteria. *Journal of Clinical Psychology, 39*(6), 985–988.

Gebhardt, J. H. (2004). *A correlational study of the developmental test of visual motor integration as kindergarten screening measure to Gates MacGinitie reading test and TerraNova test performance in grades K through four (Doctoral dissertation*. Widener University.

Geertsen, S. S., Thomas, R., Larsen, M. N., Dahn, I. M., Andersen, J. N., Krause-Jensen, M., … Krustrup, P. (2016). Motor skills and exercise capacity are associated with objective measures of cognitive functions and academic performance in preadolescent children. *PLoS One, 11*(8), Article e0161960.

Geis, R. (1971). The prediction and prevention of reading failure. Retrieved from https://eric.ed.gov/?id=ED067620.

Glidden, R. A. (2000). The validity of the Wide range assessment of visual motor abilities (WRAVMA) in differentiating children with learning disabilities. Retrieved from https://www.elibrary.ru/item.asp?id=5465471.

Greenburg, J. E., Carlson, A. G., Kim, H., Curby, T. W., & Winsler, A. (2020). Early visual-spatial integration skills predict elementary school achievement among low-income, ethnically diverse children. *Early Education and Development, 31*(2), 234–252.

Hamilton, B. S. (2001). *A correlation study of visual motor integration and reading*. Doctoral dissertation. University of Sarasota.

Hanson, G. H. (1969). Relationships among audiological status, linguistic skills, visual-motor perception, and academic achievement of deaf children. Retrieved from https://eric.ed.gov/?id=ED034349.

Hasler, H. M., & Akshoomoff, N. (2019). Mathematics ability and related skills in preschoolers born very preterm. *Child Neuropsychology, 25*(2), 162–178.

Hernández Finch, M. E., Speirs Neumeister, K. L., Burney, V. H., & Cook, A. L. (2014). The relationship of cognitive and executive functioning with achievement in gifted kindergarten children. *Gifted Child Quarterly, 58*(3), 167–182.

Hick, T. L. (1970). Response of migrant children to outdoor education. Retrieved from https://eric.ed.gov/?id=ED048988.

Hinshaw, S. P., Carte, E. T., & Morrison, D. C. (1986). Concurrent prediction of academic achievement in reading disabled children: The role of neuropsychological and intellectual measures at different ages. *International Journal of Clinical Neuropsychology, 8*(1), 3–8.

Hopkins, S., Black, A. A., White, S. L., & Wood, J. M. (2019). Visual information processing skills are associated with academic performance in Grade 2 school children. *Acta Ophthalmologica, 97*(8), e1141–e1148.

Horn, W. F., & O'Donnell, J. P. (1984). Early identification of learning disabilities: A comparison of two methods. *Journal of Educational Psychology, 76*(6), 1106.

Kaemingk, K. L., Carey, M. E., Moore, I. M., Herzer, M., & Hutter, J. J. (2004). Math weaknesses in survivors of acute lymphoblastic leukemia compared to healthy children. *Child Neuropsychology, 10*(1), 14–23.

Karlsdottir, R., & Stefansson, T. (2003). Predicting performance in primary school subjects. *Perceptual and Motor Skills, 97*(3), 1058–1060.

Kastner, J. W., May, W., & Hildman, L. (2001). Relationship between language skills and academic achievement in first grade. *Perceptual and Motor Skills, 92*(2), 381–390.

Klein, A. E. (1978). The validity of the Beery Test of Visual-Motor Integration in predicting achievement in kindergarten, first, and second grades. *Educational and Psychological Measurement, 38*(2), 457–461.

Kurdek, L. A., & Sinclair, R. J. (2001). Predicting reading and mathematics achievement in fourth-grade children from kindergarten readiness scores. *Journal of Educational Psychology, 93*(3), 451.

Lachance, J. A., & Mazzocco, M. M. (2006). A longitudinal analysis of sex differences in math and spatial skills in primary school age children. *Learning and Individual Differences, 16*(3), 195–216.

Leton, D. A. (1962). Visual-motor capacities and ocular efficiency in reading. *Perceptual and Motor Skills, 15*(2), 407–432.

Lindgren, S. D. (1978). Finger localization and the prediction of reading disability. *Cortex, 14*(1), 87–101.

Majsterek, D. J., & Lord, E. N. (1991). An evaluation of the PPVT-R and VMI for screening preschoolers who are at risk for reading disabilities. *Diagnostique, 16*(2–3), 173–179.

Mati-Zissi, H., & Zafiropoulou, M. (2003). Visuomotor coordination and visuospatial working memory of children with specific reading disabilities: A study using the Rey-Osterrieth complex figure. *Perceptual and Motor Skills, 97*(2), 543–546.

Mayes, S. D., Calhoun, S. L., Bixler, E. O., & Vgontzas, A. N. (2008). Nonsignificance of sleep relative to IQ and neuropsychological scores in predicting academic achievement. *Journal of Developmental and Behavioral Pediatrics, 29*(3), 206.
Memisevic, H., Biscevic, I., & Pasalic, A. (2018). Predictors of math achievement in elementary school students grades 1-3. *Acta Neuropsychologica, 16*(3).
Memiş, A., & Sivri, D. A. (2016). The analysis of reading skills and visual perception levels of first grade Turkish students. *Journal of Education and Training Studies, 4*(8), 161–166.
Meng, Z. L., Wydell, T. N., & Bi, H. Y. (2019). Visual-motor integration and reading Chinese in children with/without dyslexia. *Reading and Writing, 32*(2), 493–510.
Moore, I. M. K., Lupo, P. J., Insel, K., Harris, L. L., Pasvogel, A., Koerner, K. M., … Hockenberry, M. J. (2016). Neurocognitive predictors of academic outcomes among childhood leukemia survivors. *Cancer Nursing, 39*(4), 255.
Nesbitt, K. T., Fuhs, M. W., & Farran, D. C. (2019). Stability and instability in the co-development of mathematics, executive function skills, and visual-motor integration from prekindergarten to first grade. *Early Childhood Research Quarterly, 46*, 262–274.
Newton, K. R. (1966). *A suggested method for pre-school identification of potential reading disability*.
Nielson, S., & Sapp, G. L. (1991). Bender-gestalt developmental scores: Predicting reading and mathematics achievement. *Psychological Reports, 69*(1), 39–42.
Oberer, N., Gashaj, V., & Roebers, C. M. (2018). Executive functions, visual-motor coordination, physical fitness and academic achievement: Longitudinal relations in typically developing children. *Human Movement Science, 58*, 69–79.
Oliver, K. (2013). Visual, motor, and visual-motor integration difficulties in students with autism spectrum disorders. Dissertation retrieved from https://scholarworks.gsu.edu/cgi/viewcontent.cgi?referer=https://scholar.google.com/&httpsredir=1&article=1095&context=cps_diss.
Pienaar, A. E. (2019). *The association between under-nutrition, school performance and perceptual motor functioning in first-grade South African learners: The North-West Child Health Integrated with Learning and Development study, 24*. Health SA Gesondheid.
Pieters, S., Desoete, A., Roeyers, H., Vanderswalmen, R., & Van Waelvelde, H. (2012). Behind mathematical learning disabilities: What about visual perception and motor skills? *Learning and Individual Differences, 22*(4), 498–504.
Pieters, S., Roeyers, H., Rosseel, Y., Van Waelvelde, H., & Desoete, A. (2015). Identifying subtypes among children with developmental coordination disorder and mathematical learning disabilities, using model-based clustering. *Journal of Learning Disabilities, 48*(1), 83–95.
Pitchford, N. J., Papini, C., Outhwaite, L. A., & Gulliford, A. (2016). Fine motor skills predict maths ability better than they predict reading ability in the early primary school years. *Frontiers in Psychology, 7*, 783.
Preda, C. (1997). Test of visual-motor integration: Construct validity in a comparison with the Beery-Buktenica developmental test of visual-motor integration. *Perceptual and Motor Skills, 84*(3_suppl), 1439–1443.
Richardson, E., DiBenedetto, B., Christ, A., & Press, M. (1980). Relationship of auditory and visual skills to reading retardation. *Journal of Learning Disabilities, 13*(2), 77–82.
Roberts, G., Bellinger, D., & McCormick, M. C. (2007). A cumulative risk factor model for early identification of academic difficulties in premature and low birth weight infants. *Maternal and Child Health Journal, 11*(2), 161–172.
Sandoval, J., & Hughes, G. P. (1981). *Success in nonpromoted first grade children*. Final Report.
Sapp, G. L. (1984). *Sociocultural factors and bender visual motor gestalt performance*.
Sewell, R. D. (2008). *Cognitive and behavioral correlates in mathematical ability subtypes*. Riverside: University of California.
Shepherd, C. W., Jr. (1969). Childhood chronic illness and visual motor perceptual development. *Exceptional Children, 36*(1), 39–42.
Simms, V., Clayton, S., Cragg, L., Gilmore, C., & Johnson, S. (2016). Explaining the relationship between number line estimation and mathematical achievement: The role of visuomotor integration and visuospatial skills. *Journal of Experimental Child Psychology, 145*, 22–33.
Sullivan, M. C., & McGrath, M. M. (2003). Perinatal morbidity, mild motor delay, and later school outcomes. *Developmental Medicine & Child Neurology, 45*(2), 104–112.
Taha, M. M. (2016). Structural model of the relationships among cognitive processes, visual motor integration, and academic achievement in students with mild intellectual disability (MID). *Insights Into Learning Disabilities, 13*(2), 131–150.
Tillman, C. E. (1974). A comparison of perceptual motor skill with auditory comprehension as correlates of word recognition, oral reading, and silent reading. Retieved from https://eric.ed.gov/?id=ED234354.
Wallbrown, J. D., Engin, A. W., Wallbrown, F. H., & Blaha, J. (1975). The prediction of first grade reading achievement with selected perceptual-cognitive tests. *Psychology in the Schools, 12*(2), 140–149.
Wallbrown, J. D., Wallbrown, F. H., & Engin, A. W. (1977). The validity of two clinical tests of visual-motor perception. *Journal of Clinical Psychology, 33*(2), 491–495.
Webb, J. (1985). A follow-up study of cross-cultural validity of Developmental Test of Visual-motor Integration. *Perceptual and Motor Skills, 60*(1), 167–173.
Webb, J., & Abe, K. (1984). Cross-cultural validity of the developmental test of visual-motor integration. *Perceptual and Motor Skills, 58*(1), 183–188.
Welcher, D. W., Wessel, K. W., Mellits, E. D., & Hardy, J. B. (1974). The Bender-Gestalt test as an indicator of neurological impairment in young inner-city children. *Perceptual and Motor Skills, 38*(3), 899–910.
Wright, J. A. (1976). *Relation of visual and motor perception to reading achievement among children with one year of study in school*. Doctoral dissertation. The Ohio State University.