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EMPIRICAL ARTICLE

CHILD DEVELOPMENT

Determinants of elementary-school academic achievement: Component cognitive abilities and memory integration

Alena G. Esposito[1] | **Patricia J. Bauer**[2]

[1]Department of Psychology, Clark University, Worcester, Massachusetts, USA
[2]Department of Psychology, Emory University, Atlanta, Georgia, USA

Correspondence
Alena G. Esposito, Department of Psychology, 950 Main Street, Worcester, Massachusetts 01501, USA.
Email: aesposito@clarku.edu

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Abstract

Children are on a quest for knowledge. To achieve it, children must integrate separate but related episodes of learning. The theoretical model of memory integration posits that the process is supported by component cognitive abilities. In turn, memory integration predicts accumulation of a knowledge base. We tested this model in two studies (data collected in 2016–2018) with second (8-year-olds; n = 391; 196 female; 36% Black, 27% Hispanic/Latinx, 29% White, and 8% multiracial) and third (9-year-olds; n = 282; 148 female; 36% Black, 31% Hispanic/Latinx, 27% White, and 5% multiracial) graders. The results support the theoretical model and the role of verbal comprehension in learning new information, and also indicate that verbal comprehension alone is not sufficient to build knowledge.

INTRODUCTION

A major goal of education is to support children in their quest for knowledge. A foundation of knowledge undergirds thought, language, and the acquisition of more knowledge (Goswami, 2011). Because learning opportunities are separate from one another and distributed over time, an essential task in building a knowledge base is integrating separate but related episodes of learning across time and modality. Without integrating across lessons, medium, and contexts, pieces of information would remain isolated and without the rich connections that build the foundation for future learning and academic success. In short, memory integration is a productive process that supports making meaning from separate facts (for discussion, see Bauer, 2021; Bauer et al., 2020). This analysis implies that integration of separate yet related episodes of learning is a critical component of academic success. In turn, integrating across lessons and contexts is at least partially dependent on component cognitive abilities, such as inhibitory control and verbal comprehension (see Goswami, 2011, for discussion). Thus, theoretically, component cognitive abilities predict successful memory integration and, in turn, successful memory integration predicts building a knowledge base that can be indexed through academic achievement.

Separate studies with elementary-aged children have provided support for the relation between component cognitive abilities and memory integration (Esposito & Bauer, 2018) and between memory integration and academic performance (Esposito & Bauer, 2017). However, only one study has examined the full model (Varga et al., 2019). Among other component cognitive abilities (including working memory and concept formation), only verbal comprehension predicted academic performance. Moreover, although memory integration also predicted academic performance, it was not a unique predictor of either concurrent or future academic performance, once verbal comprehension was included in the model. As the only comprehensive study of the role of component cognitive abilities and integration processes in supporting academic achievement, this study is important. Yet, because the sample size was small (n = 56), it is not clear if this result is a matter of power or whether it indicates that memory integration is not a unique predictor of academic performance in elementary aged-children. To further test the role of integration in academic performance, in the present research, we examined the relation between component cognitive abilities, memory integration, and academic performance in second graders (8-year-olds; Study 1) and third graders (9-year-olds; Study 2).

Examination of the predictors of academic achievement is more important now than ever before. The U.S. education system has made advances in effectiveness as evidenced by increases in high school graduation rates, college attendance, and science and math achievement scores (The International Association for the Evaluation of Educational Achievement [IEA], 2016; https://nces.ed.gov/timss/). Yet achievement gaps remain based on socioeconomic status, race, and ethnicity (e.g., Hung et al., 2019). These gaps are likely to increase in coming years due to the disproportionate impact of the COVID-19 pandemic on communities of color and minoritized groups (see Bailey et al., 2021; Benner & Mistry, 2020, for discussion). Thus, it is imperative to identify predictors of classroom achievement, especially for those for whom education is not equitable. Accordingly, the primary aim of this study is to identify predictors of academic performance in a sample of socioeconomically, racially, and ethnically diverse elementary school children. The major research question is whether memory integration is a unique predictor of academic performance once other component cognitive abilities are included in the predictive model.

Memory integration

Memory integration refers to the cognitive processes of creating meaning from individual facts and experiences (for discussion, see Bauer et al., 2020; Bauer et al., 2021). If these pieces of information remain separate, conceptual knowledge cannot build and learning stagnates. The focus on memory integration is justified logically and empirically. Logically, memory integration is required to bridge the gaps between separate but related learning episodes. By definition, learning episodes are distributed in time and thus the requirement for integration is the rule rather than the exception. Empirically, memory integration has been found to predict academic achievement in both children and adults, as noted above. There are a number of ways of testing memory integration, including associative (e.g., Schlichting et al., 2017) and transitive (e.g., Jensen et al., 2017) inference. In these paradigms, evidence of memory integration comes from inferences of valid indirect relations. For example, after explicitly learning that A is larger than B, and that B is larger than C, it can be inferred that A is larger than C. Inference of the indirect relation between A and C is made possible by integrating the separate yet related premises (e.g., Spalding et al., 2018).

Perhaps, most relevant to learning in the classroom is the paradigm of self-derivation of new factual knowledge through memory integration (e.g., Bauer & San Souci, 2010). In this paradigm, separate yet related episodes of new learning can be integrated with one another to derive new factual knowledge. For example, a student may learn that "liquid expands when heated" in one lesson and then that "thermometers are full of liquid" in a separate lesson. They then are equipped to derive a correct response to the question "How does a thermometer work?" through integration of the separate episodes and self-derivation of the novel fact that thermometers work because the liquid in them expands with heat. The self-derivation through memory integration paradigm has yielded information about integration processes in both the laboratory (e.g., Bauer & San Souci, 2010; Esposito & Bauer, 2018) and the classroom (e.g., Esposito & Bauer, 2017, 2019). It is especially relevant for tests of relations between integration processes and academic achievement for at least three reasons. First, successful memory integration has been observed in classrooms (e.g., Esposito & Bauer, 2017, 2019). Second, the process occurs over a range of content, including stimuli derived from school curricula (e.g., Bauer et al., 2019; Esposito et al., 2021). Third, and most importantly, memory integration as measured through the self-derivation paradigm is related to academic performance in both elementary children and college students (Esposito & Bauer, 2017; Varga et al., 2019). In summary, memory integration is entailed in the productive processes that build meaning from individual facts as measured by paradigms such as associative and transitive inference and self-derivation through integration. Although all of these productive processes may be observed in classrooms, act on curriculum-relevant materials, and relate to academic performance, only self-derivation through integration has been put to the relevant tests. Indeed, memory integration as measured through the self-derivation paradigm has been shown to be a valid model of how knowledge accumulates over time and experience (discussed in Bauer et al., 2019), making it particularly well suited to educationally relevant work.

Memory integration and component cognitive abilities

Interest in the relation between memory integration and component cognitive abilities is fueled by the need to explain individual variability in performance. Both children and adults show great individual differences in memory integration performance (e.g., Esposito & Bauer, 2018; Varga & Bauer, 2017a, 2017b). Given the relation between memory integration and academic performance, component cognitive abilities that predict academic performance may also be potential candidates for predicting individual differences in memory integration. Thus, component cognitive abilities that have a robust association with academic achievement, such as inhibitory control and working memory (see Serpell & Esposito, 2016 for review), are a target for investigation.

The research on component cognitive abilities and memory integration has yielded both developmental commonalities and differences. For example, Esposito and Bauer (2018) tested memory integration performance and component cognitive abilities in 81 children (6, 8, and 10 years) across two studies in a laboratory setting. The component cognitive abilities included verbal comprehension, long-term memory, reasoning, and several measures of executive functions including inhibitory control. Across studies and age groups, verbal comprehension emerged as the only unique predictor of memory integration performance as measured by self-derivation through integration. In a separate investigation, Varga et al. (2019) examined the relation between self-derivation through integration performance and component cognitive abilities with 8-year-old children in a school setting (n = 57). The component cognitive abilities were verbal comprehension, relational reasoning, and working memory. Again, verbal comprehension emerged as the only unique predictor of memory integration performance.

Interestingly, Varga et al. (2019) also tested an adult sample (n = 117) and found that both working memory and verbal comprehension predicted performance. Thus, across all age groups tested, verbal comprehension has emerged as a unique predictor of memory integration. In contrast, working memory was related to memory integration in adults only. However, the adult sample size was larger than the sample sizes in the child studies and may, therefore, have been better able to detect relations with working memory. Consequently, the relation between component cognitive abilities and memory integration in children remains unclear.

Memory integration and academic performance

Research examining memory integration as measured through self-derivation has indicated a relation between memory integration and academic performance. Understanding the nature of this relation may help explain individual differences in student academic performance, an important step to educational equity. Two studies, in particular, inform our understanding of the relation between memory integration and academic performance in children. The first, Esposito and Bauer (2017), examined self-derivation through integration in children across grades K-3 (age 5–10 years, n = 278) in a classroom setting. Academic measures were provided by the collaborating school system. Children in kindergarten (M = 6.08 years) struggled to integrate separate episodes of learning as evidenced by the floor-level performance on the self-derivation task. However, children in grades 1–3 (age 7–10 years) showed sufficient variation in the self-derivation task to examine relations with academic performance. In these grades, self-derivation through integration was found to be a unique predictor of both reading and math academic performance even when parent education level was included in the model. However, no other component cognitive abilities were included in this study, leaving open the question of whether memory integration is a unique predictor when including other known correlates of academic performance, such as working memory (e.g., Gathercole et al., 2003).

Second, Varga et al. (2019) examined relations between academic performance, component cognitive abilities, and memory integration with both elementary and college students (n = 57 and 117, respectively). In this study, memory integration was measured through self-derivation through integration and predicted future academic performance in college students even when the component cognitive skills of verbal comprehension and working memory were included in the model. However, as previously stated, when verbal comprehension was included in the elementary student models, memory integration was no longer a significant predictor of academic performance. It is also unknown how other factors that are associated with academic performance (inhibitory control, working memory, e.g., Serpell & Esposito, 2016; parent education level, e.g., Davis-Kean, 2005) would impact the model. The research, thus, leaves an open question of whether memory integration performance in classroom settings is a unique predictor of academic achievement when included with component cognitive abilities known to correlate with academic performance. Understanding this relation is important to better understand individual differences in academic performance and how best to support learners.

The current research

In the current research, we conducted two studies to examine the relation between component cognitive abilities, memory integration, and academic performance in school-age children. Understanding what factors contribute to building knowledge is of great importance in this age group when children are heavily engaged in the developmental task of accumulating a knowledge base. In Study 1, we assessed memory integration in second grade (M = 8 years) classrooms with a self-derivation through integration story-passage paradigm (e.g., Bauer & San Souci, 2010; Esposito & Bauer, 2017). In Study 2, we assessed memory integration in third grade (M = 9 years) classrooms using a single-sentence self-derivation through integration paradigm that allows for quadruple the trials in comparison to the story paradigm (e.g., Esposito & Bauer, 2018; Esposito et al., 2021). In both studies, we included individual component cognitive abilities and academic outcomes provided by the collaborating school. The cognitive battery included verbal comprehension, nonverbal intelligence, working memory, inhibitory control, and flexible switching. Academic measures included standardized measures in both studies. For the second graders (Study 1), we collected iReady Reading and Math scores, a computerized standardized assessment. For the third graders (Study 2), we collected State Standardized End-of-Grade Reading and Math scores. Reading and math were targeted because they are considered foundational knowledge on which further knowledge can be built and the majority of instructional time across these grade levels is devoted to these subject areas.

The research was conducted in an area of rural poverty where, overall, children do not meet state expectations for annual growth. The population has racial and ethnic diversity as well as linguistic diversity. We conducted the work within the academic environment of the children, their classrooms. Thus, the research was conducted with a population and in an area underrepresented in research, and where educational equity is of great concern.

Given the extant research examining the theoretical model and the large sample sizes here employed, the present research represents more confirmatory rather than exploratory analyses. Based on prior research regarding memory integration, we predicted that verbal comprehension will be a unique predictor of memory integration across both studies. Given the relation between working memory and memory integration in adults, as well as working memory and academic performance in children, we also predicted a positive relation between working memory and memory integration in children. Finally, although previous research has not led to a clear prediction, the necessity of integrating across lessons to build knowledge leads us to predict that memory integration will emerge as a unique predictor of academic performance even when the component cognitive abilities are included in the models.

STUDY 1

The major purpose of Study 1 was to examine the relation between component cognitive abilities, memory integration, and academic performance in a diverse sample of second-grade children (7- to 9 years) in a school setting.

Methods

Participants

The participants were drawn from a larger study of 391 (196 female, 192 male, 3 did not report) students in second-grade classrooms that included academic data (math $n = 379$; reading $n = 137$; $M = 8$ years; range = 76–120 months) in a rural public school in the Southeastern United States. This research is made possible through an ongoing collaboration with a local school system and is the same population from which the sample was recruited for Varga et al. (2019), allowing us to revisit the research questions within the same diverse community with a larger sample size. When possible, models were run with full available data. Data were collected over three consecutive years. Each year, consent forms were sent home through Parent Contact folders that are the schools typical means of communication with parents/guardians. Only students whose parents/guardians returned signed consent forms were included (approximately 69% of the population over the 3 years). All students with parental/guardian consent who contributed data to an analysis were included. However, due to absences and other typical interruptions that occur during school data collection (e.g., child absence on 1 day of data collection), not all children contributed data to all measures. In addition, during the course of the 3 years of data collection, the school system utilized different school-wide measures of reading performance. Due to an inability to appropriately equate performance across these measures, we chose instead to evaluate academic performance with the measure for which we had the largest sample size ($n = 137$). We are also missing one task of inhibitory control in Year 1 of the study (see Table 1, Panel A, for report of measures and n by year). The sample sizes are reported for each analyses.

Approximately 93% of participants returned a family demographic survey. Reflecting the diversity of the community, based on parental report, the sample was 36% Black, 27% Hispanic/Latinx, 29% White, and

TABLE 1 Measures and sample sizes

	Year		
	1	2	3
Panel A—Study 1			
Self-derivation	$n = 121$	$n = 92$	$n = 122$
Woodcock-Muñoz	$n = 78$	$n = 75$	$n = 103$
Nonverbal intelligence	$n = 107$	$n = 75$	$n = 116$
TMT	$n = 80$	$n = 70$	$n = 114$
BST	$n = 81$	$n = 80$	$n = 117$
Simon	—	$n = 75$	$n = 115$
GNG	$n = 81$	$n = 74$	$n = 117$
Backward Corsi	$n = 81$	$n = 71$	$n = 114$
iReady Math	$n = 146$	$n = 98$	$n = 135$
iReady Reading	—	—	$n = 137$
Panel B—Study 2			
Self-derivation	$n = 113$	$n = 130$	—
Woodcock-Muñoz	$n = 87$	$n = 112$	—
Nonverbal intelligence	$n = 120$	$n = 119$	—
TMT	$n = 88$	$n = 109$	—
BST	$n = 88$	$n = 118$	—
GNG	$n = 89$	$n = 111$	—
Backward Corsi	$n = 87$	$n = 113$	—
EOG Math	$n = 132$	$n = 141$	—
EOG Reading	$n = 132$	$n = 141$	—

Note: BST, bivalent shape task; EOG, end-of-grade; GNG, go/no-go task; TMT, trail making task.

8% multiracial, with less than a percent other or unreported. Approximately 86% of children in the community qualified for federally funded school lunch assistance during the 3 years of data collection. Of the participants whose families reported primary caregiver education, 45% had a high school education or less, 25% had some training beyond high school, 13% had a technical or associates degree, 17% had a college bachelor degree or additional education beyond a college degree. Participating teachers were thanked with a $20 gift card, parents were thanked with a $10 gift card, and participating children were thanked with a small school supply item (e.g., eraser). The Institutional Review Board and participating school system School Board reviewed and approved all study protocol and procedures for this and the second study.

Stimuli

The stimuli were eight novel facts that formed four pairs of related facts. Within a pair, the two facts were related and could be combined to generate a novel integration fact. The stimuli were pilot tested to ensure both that the stem and integration facts were novel to children in the target age range and that both stem facts were necessary for production of the integration facts. Pilot testing was conducted in a different collaborating school to mimic the conditions of testing in the classroom, with follow-up group testing in the laboratory to fine-tune the stimuli.

The facts were featured in text passages resembling picture stories (see Bauer & San Souci, 2010, for an example) presented through Power Point®. This digital book format has been used in previous classroom research (e.g., Esposito & Bauer, 2017; Varga et al., 2019). The passages were 81–89 words in length, distributed over four illustrations. Illustrations were hand-drawn and depicted the main actions of the text, projected on a whiteboard while pre-recorded text passages played. The text was not visible to the students. The passages all followed the structure of a character learning a true but novel fact in the course of a short story; story pairs had different animals as the main characters. Only the individual facts were included in the passages; the integration facts were not presented. Stimuli were modified as necessary between years of data collection to reflect changes to the curriculum. No children who repeated second grade were included in analyses, thus no children contributed to the data in more than 1 year.

Materials

Component cognitive abilities

We investigated the cognitive correlates with several standard measures, including verbal comprehension measure, an adapted nonverbal intelligence measure, and measures of inhibitory control, cognitive flexibility, and working memory (see Table 1, Panel A; Table 2; see also Supplemental Materials for additional task information).

Academic Measures

Academic measures were collected from the school and consist of school administered formative and summative assessments in math and reading achievement. The iReady Mathematics Diagnostic is computer adaptive and aligned to grade level standards. It takes 45–60 min to complete and the final assessment of the year is considered the summative. Several domains are assessed, such as algebraic thinking and geometry. We analyzed the overall score for the summative assessment. The scores ranged from 5 to 725. This measure was available for all 3 years of data collection.

The school system transitioned from one reading assessment system to another during the course of the data collection as a staggered transition. The different reading assessments cannot be equated, so we instead chose to analyze the assessment to which the school system transitioned (the iReady reading), both because we had the most data for this assessment and because the school system deemed them the most valid for assessing their students. The iReady Reading Diagnostic is a computerized adaptive test that is aligned to the school systems reading standards. It measures fundamental skills, such as phoneme awareness, as well as grade level standards in areas of decoding, vocabulary, and reading comprehension. The test is taken in the classroom and takes approximately 45–60 min. It is administered several times a year with the last assessment considered summative. The results can be reported as scores within domains or as overall. We analyzed the overall score for the summative assessment, which ranges from 155 to 810 for this sample. This measure was available for one of the 3 years of data collection.

Procedure

There were two data collection sessions, one in the classroom followed by a second individual assessment approximately a week later. Session 1, the classroom session, included all group-administered assessments. All children in the classroom participated in the Session 1 self-derivation through integration task, but data were only analyzed from those whose parents had signed consent. Approximately 1 week later, children for whom we had parental consent to participate were invited to leave their classroom to go to a separate classroom reserved for our purposes and meet one-on-one with a research assistant to complete the individual assessments. All

TABLE 2 Measures descriptions

Construct	Assessment name	Description	Reliability
Verbal comprehension	Woodcock-Munoz Language Survey—Revised Normative Update (WMLS- R NU)	The English Verbal Comprehension test of the *WMLS®—R NU* (Schrank & Woodcock, 2009). We administered two subtests: Vocabulary (Test 1) and Analogies (Test 2). Participants received one point for each correctly answered item and the test was discontinued when six consecutive items were answered incorrectly. Scores were summed for both Test 1 and Test 2, resulting in one verbal comprehension score. This measure was administered all 3 years	Mdn = .92 from 2 to 80 years (Schrank et al., 2010)
Nonverbal intelligence measure	Adapted version of the *Test of Nonverbal Intelligence—4th edition* (*$TONI_4$*)	The *$TONI_4$* (Brown et al., 2010) is designed to be language-free. Individuals are shown a series of patterns and asked to choose an image that completes each puzzle. We administered the task in group format by showing the full class each image and then providing five options (labeled with letters) to choose from to complete the puzzle (the original task has 4–6 options). Children responded individually with individual response devices ("clickers"). The score was the sum total of correctly completed puzzles. This measure was administered in all 3 years of data collection	Original test Mdn = .88 for school age children (Brown et al., 2010)
Cognitive flexibility	Trail making task (TMT) via Psychology Experiment Building Language (PEBL; Mueller, 2011, Mueller, 2010)	We administered a version of the TMT developed for children (e.g. Bowie & Harvey, 2006; Delis, Kaplan, & Krames, 2001; Mueller, 2011, Mueller, 2010; Reitan, 1971). Children completed 3 trails by putting items in order. The first trail required numeration (1–16; 1–2-3…), followed by alphabetical sequencing (A-K; A-B-C…), and finally an alternating sequence of letter and number (1-A-2-B-3-C). Response time for the last trail is the measure of cognitive flexibility. This task was administered in all 3 years of data collection	The PEBL version of this task has been tested for validity (Piper et al., 2012) and higher test–retest reliability than paper versions (r = .61–.74 vs r = .45, respectively; Piper et al., 2016)
Inhibitory control	Bivalent Shape Task via Psychology Experiment Building Language (PEBL; Mueller, 2011, Mueller, 2010)	The Bivalent Shape Task is a nonverbal analog to the Stroop Task, developed by Esposito et al. (2013). It requires children to match the shape between objects and ignore the highly salient color. The dependent variable was mean reaction time on correct incongruent trials (color and shape mismatch)	Reliable across a 1-week period with this age group (e.g., Esposito, 2021; Esposito & Bauer, 2018)
Inhibitory control	Simon Task via Psychology Experiment Building Language (PEBL; Mueller, 2011, Mueller, 2010)	The Simon task measures stimulus–response conflict in which children need to ignore the salient physical location of a shape on the screen and instead respond to color (Lu & Proctor, 1995; Simon & Wolf, 1963). The dependent variable was the mean reaction times for correct trials for incongruent trial types. This task was collected in two of the 3 years of data collection	Cronbach's alpha = .88, with adults in short form; Cevada et al. (2019); validated as a marker of attention deficit in children (e.g., Mullane et al., 2009)
Inhibitory control	Go/No-Go Task via Psychology Experiment Building Language (PEBL; Mueller, 2011, Mueller, 2010)	The Go/No-Go Task (Archibald & Kerns, 1999) was adapted for touchscreen use (Mueller, 2010). Participants were asked to tap the screen in response to the target stimulus. The target stimulus appeared with 80% frequency and nontarget with 20% frequency. The dependent variable taken from this measure was total errors	Validated with parent and teacher reports (Bezdjian et al., 2009) and has acceptable test–retest reliability (pr^2 = .40, p < .001; Kindlon, Mezzacappa, & Earls, 1995)
Working memory	Backward Corsi Blocks via Psychology Experiment Building Language (PEBL; Mueller, 2011, Mueller, 2010)	The backward Corsi block task was used to assess working memory (Milner, 1971). Participants must hold a sequence in mind while performing a mental operation on the sequence (reversing the sequence). Participants respond by touching the squares. The sequence begins with two blocks in each trial and increases by one block after two correctly completed trials. If neither trial at a given level is completed correctly, the task terminates. We recorded the total score of correct number of touches made during the task	*M* range 3.92–4.92, *SDs* 0.56–0.77 (McLean & Hitch, 1999)

research assistants had been extensively trained and fidelity to the protocol was monitored by the first author throughout protocol administration.

Session 1

The 45-min classroom sessions were conducted in three phases. In Phase 1, students heard the first of each of the four pairs of text passages while the accompanying illustrations were projected on the classroom screen (approximately 4′ by 6′). Students were then engaged in an unrelated buffer activity for approximately 10 min. Phase 2 began immediately following this buffer activity. In Phase 2, the children heard the second of each of the four pairs of text passages while the illustrations were again projected. Students then completed the nonverbal intelligence measure, which lasted approximately 10 min and provided a buffer between Phases 2 and 3. For both phases, the audio tracks were prerecorded and advanced automatically, ensuring consistent timing across classrooms. The text passages were presented in one of four predetermined random orders and each order was used approximately equally across classrooms.

In Phase 3, the children were tested for self-derivation of new factual knowledge through integration of the members of the pairs of related facts. Open-ended questions were presented in written format to the class and the questions were read aloud by an experimenter. Children were asked to write their answer on the recorded sheet. All children were thanked for their participation with a colorful pencil.

Session 2

Individual testing took place approximately 1 week after the classroom self-derivation task. Children were escorted in small groups to an alternative classroom in the school to meet one-on-one with a research assistant. We investigated the cognitive correlates with several standard measures. In this individual testing session, we had a verbal comprehension measure and we used computer-based measures of inhibitory control, cognitive flexibility, and working memory (see Table 1, Panel A). Measures were administered in a fixed order: computerized measures (randomized, but always concluding with working memory; Trail Making Task (TMT), Bivalent Shape Task (BST), Simon task, the Go-No-Go task (GNG), and the Backward Corsi Blocks task) followed by verbal comprehension (*Woodcock-Muñoz Language Survey®—Revised Normative Update*; Schrank & Woodcock, 2009). Descriptions of each task, and their reliability and validity measures, are provided in Table 2 (see also Supplemental Materials). When testing was complete, children chose a small thank you item (e.g., eraser) and were escorted back to class.

Scoring

In the self-derivation through integration task, children received 1 point for each correct response for a total possible score of up to 4 points. This was then converted to a portion correct. Portion correct allowed us to include data for the rare instance where there was a disruption during Session 1 that required us to eliminate an integration question from analyses (e.g., child shouts out answer during testing; affected 31 children).

RESULTS

The results are reported in two sections (see Table 3, Panel A for means). First, we examined the relation between the component cognitive abilities and memory integration as measured by self-derivation through integration performance. Second, we examined whether memory integration performance predicts academic performance above and beyond component cognitive abilities for the subset of children for which academic measures were available. Due to the design of the study, a large number of planned-missingness is present in the data (Enders, 2010). We conducted standard multiple regression models with the complete data (see Supplemental Materials, Table 1, for full regression model details), and validated the results by then estimating the multiple regression models in the structural equation modeling framework using full information maximum likelihood, which assumes the data are missing at random (reported in Supplemental Materials). The SEM framework analyses allowed us to examine the research questions while retaining every observation available. Consistency across the regression and SEM framework models indicates robust effects, although the higher power of the SEM framework can detect predictors with smaller effect sizes and, therefore, may result in more significant predictors. All analyses were conducted in JMP® Pro version 16.0 (SAS Institute Inc., 1989–2021) and were two-tailed. For all models, predictors included memory integration, verbal comprehension, nonverbal intelligence, working memory, inhibition cognitive flexibility, and primary caregiver education. All predictor variables were centered, with the exception of primary caregiver education which is a categorical variable with a meaningful 0.

Component cognitive abilities and memory integration

We first analyzed the relation between the component cognitive abilities and the memory integration measure. Multiple regression analysis was used to examine whether component cognitive abilities significantly predicted children's memory integration performance for

TABLE 3 Measure means and standard deviations

	Year 1	2	3	Overall
	M (SD)	M (SD)	M (SD)	M (SD)
Panel A—Study 1				
Self-derivation (score)	0.42 (.31)	0.31 (0.23)	0.35 (0.30)	0.32 (0.30)
Woodcock-Muñoz (score)	44.08 (7.38)	44.08 (7.36)	42.76 (7.58)	43.65 (7.69)
Nonverbal intelligence (score)	10.11 (2.71)	12.05 (2.44)	8.82 (2.91)	10.10 (3.00)
TMT (s)	54.02 (27.54)	49.76 (23.60)	52.65 (26.27)	52.31 (25.95)
BST (ms)	1090.48 (171.36)	1051.11 (188.30)	1051.06 (170.21)	1066.17 (183.47)
Simon (ms)	—	1079.72 (154.39)	1092.84 (194.73)	1105.18 (270.49)
GNG (score)	6.33 (4.32)	3.54 (1.97)	3.96 (3.17)	4.92 (3.59)
Backward Corsi (score)	22.54 (14.79)	15.99 (13.94)	17.34 (13.57)	19.45 (14.79)
iReady Math (score)	384.45 (139.16)	413.93 (136.47)	357.19 (131.87)	382.36 (137.33)
iReady Reading (score)	—	—	493.54 (183.06)	493.54 (183.06)
Panel B—Study 2				
Self-derivation (score)	0.17 (0.12)	0.09 (0.13)	—	0.13 (0.13)
Woodcock-Muñoz (score)	47.11 (7.17)	46.91 (7.75)	—	47.00 (7.48)
Nonverbal intelligence (score)	11.53 (2.24)	13.11 (3.15)	—	12.32 (2.84)
TMT (s)	47.91 (20.78)	45.72 (27.65)	—	46.70 (24.79)
BST (ms)	1014.61 (192.71)	1009.63 (186.03)	—	1011.75 (188.47)
GNG (score)	4.99 (3.49)	2.86 (2.10)	—	3.81 (2.99)
Backward Corsi (score)	26.97 (17.17)	25.76 (17.13)	—	26.29 (17.12)
EOG Math (score)	446.78 (9.37)	448.01 (10.01)	—	447.42 (9.72)
EOG Reading (score)	435.45 (9.40)	436.78 (8.79)	—	436.14 (9.08)

Note: BST, bivalent shape task; EOG, end-of-grade; GNG, go/no-go task; TMT, trail making task.

the subset of the sample for which there were no missing data within the variables of interest ($n = 125$). The results of the regression indicated that the model predicted 16% of the variance ($R^2 = .16$, $F[8, 124] = 2.81$, $p = .007$). The only cognitive measure that was a significant predictor was verbal comprehension ($p = .002$, $\beta = .30$), such that for one standard deviation increase in children's verbal comprehension, their memory integration performance increased, on average, by .30 standard deviation units. The pattern of results was the same when estimating the multiple regression model in SEM (see Supplemental Materials).

Predicting academic performance

We next examined whether memory integration predicted academic achievement in a model including memory integration and all component cognitive abilities as predictors using multiple regression. Separate regression models were used to predict math performance and reading performance. Over the years of this investigation, the school system utilized the iReady Math assessment to document the growth in math performance in the second grade ($n = 379$). Regarding reading performance, the school system used a different measure each year, transitioning to iReady Reading in the final year of data collection, resulting in a smaller sample size for examining reading performance ($n = 137$). The pattern of results for both math and reading were the same when estimating the multiple regression models in SEM (see Supplemental Materials).

Multiple regression was used to predict math performance for the subset of the sample for which there were no missing data ($n = 125$). The results of the regression indicated that the model predicted 51% of the variance ($R^2 = .51$, $F[9, 124] = 13.12$, $p < .001$). Significant predictors were verbal comprehension ($\beta = .25$, $p < .001$), nonverbal intelligence ($\beta = .31$, $p < .001$), working memory ($\beta = .17$, $p = .01$), and memory integration ($\beta = .27$, $p < .001$), such that a standard deviation increase in each of these predictors resulted in, on average, .25, .30, .17, and .27 increases in math scores, respectively.

In the second model, predicting reading achievement, multiple regression was again used to predict performance for the subset of the sample for which there were no missing data ($n = 78$). The results of the regression indicated that the model predicted 35% of the variance ($R^2 = .35$, $F[9, 77] = 4.05$, $p < .001$). In this model, the only significant predictor was memory integration ($\beta = .32$, $p = .006$), such that a standard deviation increase in memory integration resulted in, on average, a .32 increase in student reading score.

Discussion

The aims of Study 1 were to identify the predictors of memory integration and to examine whether memory integration is a significant predictor of academic performance once component cognitive abilities were included in the model. In regards to the first aim, the results replicated studies conducted with children in the laboratory and classroom setting. Across self-derivation paradigms, verbal comprehension consistently emerged as a unique predictor of self-derivation through integration (e.g., Bauer et al., 2016; Esposito & Bauer, 2018; Varga & Bauer, 2014, for laboratory studies and Varga et al., 2019, Study 2, for classroom study). The current study examined predictors of memory integration with a sample size of over 380 for the SEM models and included many additional potential cognitive correlates in the model, indicating that this finding is robust indeed.

The consistent emergence of verbal comprehension as the only unique predictor of memory integration in the regression differs from adult memory integration performance in that both verbal comprehension and working memory emerged as significant predictors (Varga et al., 2019). These finding lend weight to the interpretation that the difference in predictors between children and adults found in Varga et al. (2019) is developmental in nature and not due to insufficient power to detect a significant effect. However, it also is important to note that the memory integration testing paradigm differed between the two studies. Adults were tested with a single sentence paradigm in which each word of the sentence was presented on the screen individually followed by the next word of the sentence (Varga et al., 2019). In contrast, in the current study, children were presented with a story in continuous form. A direction for future research is to investigate whether the protocol utilized in (removed for masked review) requires more working memory, particularly at encoding.

The work also provides insight into the relation between memory integration and academic performance. Like previous studies, we found a relation between memory integration and academic performance (e.g., Esposito & Bauer, 2017). Unlike the previous study that included cognitive correlates (Varga et al., 2019), this relation remained once additional component cognitive abilities were included. Varga et al. (2019) found that self-derivation was a unique predictor of academic performance in adults, but not in children. The current academic performance results suggest that the null findings in the previous study may be due to an underpowered model rather than a developmental difference between adults and children, particularly in that the sample was drawn from the same community.

In summary, verbal comprehension is a robust predictor of memory integration and memory integration remains a unique predictor of academic performance when component cognitive abilities are included in the model. These results support the importance of integration as a focus to support academic achievement. In the second study, we addressed two limitations of Study 1. First, there were only four trials per participant, limiting variability. Second, the trials were heavily supported by a story structure including illustrations. The high-support structure limits the generalizability of the findings. Both limitations are addressed in Study 2.

STUDY 2

The major purpose of Study 2 was to examine the relation between component cognitive abilities, memory integration, and academic performance with a larger number of memory integration trials and fewer supports included in the memory integration measure. We transitioned to third-grade children (8–10 years), still in the school setting, to provide another test of these relations and expand the age range over which the findings could generalize.

Methods

Participants

The participants were 282 (148 female) students in third-grade classrooms (M = 9.05 years; range = 102–123 months) in the same public school as Study 1. Data were collected over 2 consecutive years. The current analyses represent a subset of a larger study for which individual component cognitive abilities were available. Consent was obtained in the same manner as Study 1. Only the students whose parents/guardians returned signed consent forms were included (approximately 67% of the population over the 2 years). All students with parental/guardian consent who contributed data to an analyses were included. Because the data were collected in the same school, children could have participated in both Study 1 and Study 2. In total, 101 children participated in both studies. No practice effects were anticipated based on specific examination of practice effects over a 1-week delay with this age group (Esposito & Bauer, 2018) and over a 1-year delay within this population (Dugan & Bauer, 2022). As well, students who participated in both second and third grade had a full year between studies. Both the stimuli and protocol differed between grade levels, thus no children saw the stimuli twice. None of the data from the 101 overlapping children were included in the regression models. The overlap in samples impacted the models run in SEM only. The sample sizes are reported for each analysis.

All participating children returned a family demographic survey. Reflecting the diversity of the community, based on parental report, the sample was 36% Black, 31% Hispanic/Latinx, 27% White, and 5% multiracial, with less than a percent other or unreported. Approximately 84% of children in the community qualified for federally funded school lunch assistance during the 2 years of data collection. Primary caregiver education was reported as 43% had a high school education or less, 23% had some training beyond high school, 16% had a technical or associates degree, 18% had a college bachelor degree or education beyond a college degree. Participants were thanked as in Study 1.

Stimuli

The stimuli were 32 novel "stem" facts that could be integrated to create 16 novel "integration" facts. Facts were presented as written text in a Turning Point® presentation including a recording of the facts being read aloud. The facts were presented without a supportive story and there were no illustrations. Preliminary testing revealed that both stem facts were necessary for production of the integration facts and facts were novel to children in the target age range. The paradigm was validated in laboratory studies with the same age range (e.g., Esposito & Bauer, 2018). As in Study 1, over the years of data collection, small modifications to the stimuli were made as needed to reflect changes in the school curriculum. No children who repeated grade 3 were included in the analyses, thus no children saw the stimuli more than once.

Materials

Component cognitive abilities

The Component cognitive abilities materials were the same as in Study 1, with the exception that the Simon task was not included. All tasks were administered in both years (see Table 1, Panel B, and Table 2).

Academic Measures

Beginning in the third grade, all students in the public schools in the state in which the data were collected take a state-standardized assessment in reading and mathematics based on grade-level curriculum (https://www.dpi.nc.gov/districts-schools/testing-and-school-accountability/state-tests#end-of-grade-(eog)-tests). We recorded performance on the End-of-Grade standardized math (EOG math) and reading (EOG reading) tests. The math score has a range of 429–472 and the reading score has a range of 418–461, resulting in a single math score and a single reading score. Both measures were administered both years of data collection.

Procedure

As in Study 1, participants completed two sessions spaced approximately 1 week apart with the first session being in their classrooms. Classroom test sessions were, again, conducted by one of two teams including the first author and three research assistants. Session 2 was conducted in a spare classroom with children meeting individually with one of 12 undergraduate research assistants. Experimenters followed a detailed protocol with the first author supervising to ensure protocol fidelity.

Session 1

Similar to Study 1, the 45-min classroom sessions were conducted in three phases. In Phase 1, students heard the first of each of the 16 pairs of facts. The facts were prerecorded audio files that played as the written text was projected on the classroom screen (approximately 4′ by 6′). Students then completed the nonverbal intelligence measure, which lasted approximately 10 min. Phase 2 began immediately following. In Phase 2, the children heard the second of each of the 16 pairs of facts while the texts were again projected. There was then an unrelated buffer activity of approximately 10 min. For both phases, the prerecorded audio tracks advanced automatically to ensure consistent timing across classrooms. The facts were presented in one of four predetermined random orders and each order was used approximately equally across classrooms.

Phase 3 was the testing phase. The children were tested for self-derivation of new factual knowledge through integration of the members of the pairs of related facts. Open-ended questions were presented in written format to the class. Children all had the same questions, but there were four predetermined random orders. Children sitting adjacent did not have the same version, which discouraged answer sharing. Children read the questions and wrote their answer independently. All children were thanked for their participation with a mechanical pencil.

Session 2

As in Study 1, individual testing took place approximately 1 week after the Session 1. Children met one-on-one with an experimenter in a room provided by the school for this purpose. Measures were administered in the same fixed order: computerized measures (randomized- with the exception of working memory which was always last) and then verbal comprehension. Children chose a small item (e.g., eraser) as a thank you when they were finished.

Scoring

Children received 1 point for each correct response. Thus, they could score up to 16 on integration fact questions. As in Study 1, this was then converted to a portion correct so as to account for the classes that had interruptions during testing or an error in protocol (i.e., reading the integration fact aloud) reducing the number of test questions from 16 to 15 (no class lost more than one question; affected 106 children).

RESULTS

The results are again reported in two sections (see Table 3, Panel B for means). We first examined the relation between the component cognitive abilities and memory integration performance. We next examined whether memory integration performance predicts academic performance above and beyond component cognitive abilities. As in Study 1, a large number of planned-missingness is present in the data. We conducted standard multiple regression models with the complete data, and validated the results by then estimating the multiple regression models in the structural equation modeling framework using full information maximum likelihood, which assumes the data are missing at random (see Supplemental Materials). Consistency between the two methods indicates robust effects, although it is expected that the higher power of the SEM framework may identify additional predictors with smaller effect sizes than can be detected with the regression model. All analyses were conducted in JMP® Pro version 16.0 (SAS Institute Inc., 1989–2021) and were two-tailed. For all models, predictors included memory integration, verbal comprehension, nonverbal intelligence, working memory, inhibition, cognitive flexibility, and primary caregiver education. All predictor variables were centered with the exception of primary caregiver education, which was categorical variable with a meaningful 0.

Component cognitive abilities and memory integration

We used multiple regression analysis to examine whether component cognitive abilities significantly predicted children's memory integration performance for the subset of the sample for which there were no missing data within the variables of interest (n = 145). The results of the regression indicated that the model predicted 34% of the variance ($R^2 = .34$, $F[7, 144] = 10.34$, $p < .001$). The only cognitive measure that was a significant predictor was verbal comprehension ($\beta = .54$, $p < .001$), such that a one standard deviation unit increase in verbal comprehension, resulted in a .54 standard deviation unit increase in memory integration performance. The pattern of results was the same when estimating the multiple regression models with SEM (see Supplemental Materials).

Predicting academic performance

We next examined whether memory integration predicted academic achievement in a multiple regression model including all component cognitive abilities. Separate regression models were used to predict math performance and reading performance, both assessed using state-mandated standardized year-end assessment. The pattern of results for both math and reading were the same when estimating the multiple regression models in SEM (see Supplemental Materials).

The first model predicted math performance for the subset of the sample for which there were no missing data (n = 141). The results of the regression indicated that the model predicted 41% of the variance ($R^2 = .41$, $F[8, 140] = 11.19$, $p < .001$). Significant predictors were verbal comprehension ($\beta = .20$, $p = .02$), nonverbal intelligence ($\beta = .21$, $p = .004$), working memory ($\beta = .15$, $p = .03$), and memory integration ($\beta = .25$, $p = .003$). These results suggest that, for every standard deviation unit increase in the predictors, math performance increased by .20, .21, .15, and .25 standard deviation units, respectively.

In the second model, predicting reading achievement, multiple regression again was used to predict performance for the subset of the sample for which there were no missing data (n = 141). The results of the regression indicated that the model predicted 48% of the variance ($R^2 = .48$, $F[8, 140] = 14.93$, $p < .001$). Significant predictors were verbal comprehension ($\beta = .40$, $p < .001$), nonverbal intelligence ($\beta = .18$, $p = .008$), and memory integration ($\beta = .22$, $p = .006$), such that a standard deviation increase in each of these predictors resulted in, on average, the reading score increased by .40, .18, and .22, respectively.

Discussion

The aims of Study 2 were to identify component cognitive abilities that predict memory integration and examine whether memory integration remains a significant predictor of academic performance with component cognitive abilities in the model. This was examined with a single-sentence self-derivation paradigm that offered quadruple the number of trials and less support compared to the story-structure used in Study 1. The results of Study 2 are remarkably consistent to Study 1, especially given the changes in the protocol (though we note there was overlap in the samples; data from children in both studies were not included in the regression models, but only in the SEM models). Verbal comprehension again emerged as the only unique predictor of memory integration in the regression model and remained so in the SEM models. The predictors of math performance were verbal comprehension, nonverbal intelligence, working memory, and memory integration also replicating the results of Study 1. Reading performance was predicted by memory integration, a replication, but also by verbal comprehension, nonverbal intelligence, and working memory. Importantly, memory integration was a consistent predictor of academic performance across math and reading in this low-support paradigm.

GENERAL DISCUSSION

The current work aimed to clarify the relation between component cognitive abilities, memory integration, and academic performance in elementary school children. Across both studies, the results were consistent. Verbal comprehension is a robust predictor of memory integration in childhood, over and above other component cognitive abilities. Memory integration is a unique predictor of academic performance in both math and reading domains along with other component cognitive abilities. The results were consistent across two studies with different protocols and different measures of memory integration and academic performance (though again we note that the SEM models of Study 2 were not fully independent replications of the SEM models of Study 1, given some overlap in students in the two studies).

Component cognitive abilities and memory integration

The results lend clarity to the relation between verbal comprehension, working memory, and memory integration in children. In a previous examination of cognitive predictors of memory integration with both college students and elementary students, the results between the two age groups were not entirely consistent (Varga et al., 2019). Adult performance was predicted by verbal comprehension and working memory, whereas only verbal comprehension emerged as a unique predictor in children. It was unclear whether the difference was developmental in nature or a result of low power in the child sample. The results of this investigation add clarity to the previous null results. Verbal comprehension was a consistent and robust predictor of memory integration. With sample sizes of 391 and 282 in Studies 1 and 2, respectively (compared to Varga et al., 2019, $n = 57$), the power was more than sufficient to find even a small effect size for working memory, which did emerge in one analysis. The significant effect of working memory in one SEM framework analysis is not inconsistent with the other findings. The higher power of the complete data in the SEM framework meant that even predictors with small effect sizes could be detected. The overall message remains the same- that verbal comprehension is a strong and robust predictor of memory integration. Other component cognitive abilities, including working memory, are still likely involved, but this work supports that verbal comprehension carries the bulk of the variance.

The results of the current investigation add weight to the interpretation that the difference in predictors across age groups is developmental in nature (Varga et al., 2019 for discussion). More specifically, working memory does not begin to emerge as distinct from other fluid cognitive constructs until around the age of 8 years (Mungas et al., 2013), meaning children may not engage in the process of maintaining and transforming information in memory autonomously at this age, at least not to the same extent as adults. This conjecture is supported by studies that show children engage in the process of memory integration when prompted, whereas adults begin this process during encoding (e.g., Bauer et al., 2020; Miller-Goldwater et al., 2021; Varga & Bauer, 2017a, 2017b; Wilson & Bauer, 2021). Whereas adults likely recruit working memory as early as encoding to support potential subsequent integration, children are more likely to begin the process of integration only when prompted. Thus, adults are more likely than children to use working memory during memory integration. As well, the single word presentation utilized with the adults in Varga et al. (2019) may have increased the working memory demands at encoding, thus permitting a larger role for working memory. In both the studies reported here, text was provided in complete sentences rather than one word at a time. Future work can examine whether adults utilize working memory to the same degree with a protocol that presents text continuously. Importantly, the results of this research add to accumulating evidence that working memory does not play a large part in memory integration in elementary school-aged children. Direct tests of the role of working memory in memory integration across development await future research.

Memory integration and academic performance

Memory integration as measured through self-derivation was a consistent unique predictor of both math and reading achievement across both studies. This is noteworthy, in part, because the paradigm for testing memory integration differed between studies as did the measures of academic performance. Math performance, in particular, was consistent across studies with the same four predictors (verbal comprehension, nonverbal intelligence, working memory, and memory integration). In the models predicting reading performance, verbal comprehension and memory integration were consistent, with additional predictors reaching significance in Study 2 (nonverbal intelligence and working memory). The models also accounted for substantial variance, between 35% and 51%. The consistency across studies and large amount of variance explained underscores the importance of memory integration in learning.

The robust support for the role of memory integration in academic performance has important implications for education. The consistent relation between verbal comprehension and memory integration supports the notion that knowledge begets knowledge. However, the current results indicate that obtaining the knowledge is not enough. Knowledge of individual facts is necessary, but insufficient to build knowledge over time. The notion that knowledge must be integrated to best support academic performance is consistent with a study of domain-specific math performance. Park and Esposito (2022) found that quantitative understanding of rational numbers alone did not predict math performance, but integration across rational number notations (i.e., fractions and decimals) in 10- to 12-year-old children did. It is, thus, the integration across content that predicts academic success. Metaphorically, it is not just about money in the bank, but how you spend it. You cannot spend it if you do not have it, but it does not help to have it if you do not use it. If knowledge alone were enough, the verbal comprehension measure in the current research would account for the variance in the academic models and memory integration would not emerge as an additional unique predictor of performance. This finding implies that supporting integrating and connecting new knowledge to existing knowledge in classroom settings would benefit academic outcomes. Future research can examine what classroom practices and educational materials best support memory integration and how these benefit long-term academic performance.

In the current work, memory integration was measured with the self-derivation through integration paradigm through two different protocols (story based and single sentence). The results support the role of memory integration in academic performance as measured here in classrooms with curriculum-relevant material and with delays between “lessons” and test. A direction for future research would be to examine whether memory integration as measured by other paradigms, such as associative inference and transitive inference, would have similar or different relations to academic performance. This has been tested in studies of inference within a text, in which clauses or sentences are integrated to make inferences to support reading comprehension such as in the case of anaphoric inference and recruitment of prior knowledge (e.g., Cain & Oakhill, 1999; Graesser et al., 1994; Paris & Upton, 1976). The results of this study make evident the importance of continued work examining how memory integration contributes to learning and academic performance both within and across lessons, media, and modes of experience.

Verbal comprehension

In the current studies, verbal comprehension was part of a battery of component cognitive abilities. However, classifying this variable is difficult because it is simultaneously a component cognitive ability, an index of intelligence, and an outcome variable. In measuring knowledge acquisition and learning, an index of knowledge such as verbal comprehension could be construed as an outcome measure or result of acquired knowledge. Given the reciprocal relation between knowledge and learning, we certainly anticipate that memory integration is both predicted by *and* predicts verbal comprehension outcomes. For the purpose of this investigation, our measure of verbal comprehension was not specific to the topics that were included in the memory integration stimuli. We purposefully designed the memory integration stimuli to not overlap with the measure of verbal comprehension to ensure we were measuring verbal comprehension as general acquired knowledge rather than a specific test for prior knowledge related to the stimuli. However, a direction for future research is to investigate whether memory integration predicts growth in verbal comprehension.

The results regarding verbal comprehension are consistent with the general literature on learning (see Esposito & Bauer, 2021, for review). Verbal comprehension is often used to represent general knowledge. We know from previous research that acquired knowledge (1) supports memory strategy use, (2) provides an organizational structure to guide retrieval of information, and (3) frees cognitive resources for cognitive processes (see Bjorklund, 1987; Ornstein et al., 2008; Ornstein & Naus, 1985, for reviews). Similar results were found in a study of memory integration using an AB-AC inference paradigm (Kesteren et al., 2018). Kesteren and colleagues found that memory integration (recognition of an AC relation) improved when college students were instructed to reactivate information from the AB stimuli when presented with the AC stimuli. It is reasonable to posit verbal comprehension supports memory integration as measured through self-derivation in a similar way. By laying a foundation of knowledge and organizational structure for knowledge, retrieval is facilitated and cognitive resources can be devoted to integrating.

Limitations

This study is not without limitations. The children in this study were all 7–10 years of age and attended school in the same rural impoverished community. Whereas including participants who are not often included in research is a strength, it also limits generalizability. We do not know that these results would generalize to another age group, an urban population, or more affluent families. There also are limitations associated with working within a school system. Whereas this adds validity to the results regarding how children learn in context, it also introduces a number of constraints (i.e., time) and limitations (i.e., absences, interruptions, etc.) and tends to result in greater variability in performance. Given the educational implications of the data, we sacrificed control of the experimental setting for validity. Importantly, the study was cross-sectional and thus we have to infer developmental differences rather than observe them across childhood. This also limits our ability to examine directionality of the relation between variables of interest. Although we expect that there are bidirectional influences between verbal comprehension and memory integration, longitudinal work is needed to further explicate this relation over time. Future research can address these limitations.

CONCLUSIONS

This investigation builds on previous research clarifying the relations between component cognitive abilities, memory integration, and academic performance. The results were consistent across the two studies that had different protocols and utilized different measures of memory integration and academic performance. Verbal comprehension is a robust predictor of memory integration in elementary-aged children, over and above other component cognitive abilities. Combined with previous investigations, this study adds further support to the great importance verbal comprehension has for building knowledge. In addition, the examination yielded a unique relation between memory integration and academic performance that has not previously been found. This has important implications for education in that learning individual facts is not enough: academic achievement comes through integrating facts distributed over time.

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ORCID

Alena G. Esposito https://orcid.org/0000-0002-3321-4991

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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