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Verbal working memory predicts twice the growth rate in math skills for children from low- income homes relative to their higher-income peers

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ABSTRACT

Working memory (WM) and socioeconomic status (SES) associations with math achievement are well established, but little work has considered whether WM contributions are the same across SES strata. Here, we focus on the extent to which verbal WM predicts math differently for children in low vs. higher SES homes in the US to disentangle how these relations might play out across development in differently resourced contexts, as well as the magnitude of these relationships across SES. Using data from a nationally representative sample of 13,527 children, we estimated a parallel process model to analyze the relation among the starting points and growth of verbal WM and math skills through elementary school. A multi-group model was used to compare the relative strength of associations between verbal WM and growth in math skills between low-income and not-low-income students. Results indicated that students with higher initial verbal WM levels developed math skills faster than those with lower verbal WM levels, especially in low-income households where verbal WM's effect size was nearly double relative to estimates for children in higher-income homes. Findings highlight the importance of providing families with the necessary resources to help children thrive in adverse contexts.

Introduction

Students who start school with stronger mathematical skills continue to outperform peers who enter school with weaker skills and early math skills prove to be a stronger predictor of later academic outcomes—including later reading—than do other early academic skills including literacy and attention (Duncan et al., 2007). Can trajectories be altered for students who enter school behind their peers? Domain-general skills, such as working memory (WM)—the ability to keep multiple pieces of information in mind at a given time and manipulate, update, or operate on them—might enable some children to integrate new information more efficiently than others (Blair et al., 2016; Ribner et al., 2017); children with higher WM might learn more from the same instructional inputs (Ribner, 2020) and hence make greater than expected gains. However, mathematical skill development is variable between individual children, and influenced by several intersecting factors (e.g., educational, cultural, familial, economic) that impact their learning (Bronfenbrenner, 1986). Prior evidence has suggested that children from low-income homes tend to demonstrate poorer WM than their peers in higher socioeconomic status homes (e.g., Raver, Blair, & Willoughby, 2013), partially explaining lower performance in mathematics (Fitzpatrick, McKinnon, Blair, & Willoughby, 2014; Nesbitt, Baker-Ward, & Willoughby, 2013). While relations between WM and math are well established (see Peng, Namkung, Barnes, & Sun, 2016; Spiegel, Goodrich, Morris, Osborne, & Lonigan, 2021), it remains unclear whether this relation is the same for all children or if there are differences in magnitude for children depending on household income. Here, we explore the differential contribution of WM (specifically, verbal WM [VWM]—a domain-specific subcomponent of the broader construct of WM which supports the maintenance and updating of verbal, as opposed to visuospatial, information) in the development of children's mathematical skills throughout elementary school for children from low-income versus non-low-income homes.

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Early mathematics skills

Students who start kindergarten with relatively high levels of math skills demonstrate an advantage over peers who enter kindergarten with lower levels of math skills (Duncan et al., 2007; Watts, Duncan, Siegler, & Davis-Kean, 2014). This early mastery of basic math concepts relates to children's math performance across development, even when accounting for individual differences in domain-general skills (e.g., intelligence, language, self-regulation; Blair et al., 2016; Xenidou-Dervou et al., 2018), teacher- and classroom-level variables (e.g., classroom quality; teacher-child relationships; Blankson & Blair, 2016; Blair et al., 2016), and characteristics of home environments (e.g., Morgan, Farkas, Hillemeier, Pun, & Maczuga, 2019). Indeed, multiple large-scale longitudinal studies from three Western countries have demonstrated that early math scores are the strongest predictor of math and reading skills at numerous later time points (Ahmed, Tang, Waters, & Davis-Kean, 2019; Duncan et al., 2007; Grimm, Steele, Mashburn, Burchinal, & Pianta, 2010; Pagani, Fitzpatrick, Archambault, & Janosz, 2010; Romano, Babchishin, Pagani, & Kohen, 2010).

Further, prior work suggests early childhood is a pivotal point to examine indicators of mathematical development as mathematical skills develop hierarchically. As with literacy, later skills are dependent on earlier skills, creating a sort of staircase in mathematical skill development. Unfortunately, children demonstrate differential math skills from a very early age at the lower steps of this proverbial staircase (Claessens & Engel, 2013; Crosnoe et al., 2010). These differences in early skills cast a long shadow over children's educational experiences (Claessens, Duncan, & Engel, 2009; Duncan et al., 2007; Watts et al., 2014): Differences start early and widen over time (Byrnes & Miller-Cotto, 2016). Preschoolers' number knowledge, counting abilities, and understanding of basic arithmetic operations relates to students' subsequent mathematical achievement throughout their school careers (Claessens & Engel, 2013; Duncan et al., 2007; Geary, 2013; Jordan, Kaplan, Ramineni, & Locuniak, 2009; Stevenson & Newman, 1986; Watts et al., 2014). Thus, it is not surprising that most recommendations for supporting early math skills include providing support as early as possible. One construct in particular that has been shown to provide support for the development of mathematical skills early on is children's developing WM skills (Ellis et al., 2021; Miller-Cotto & Byrnes, 2020; Ribner, Ahmed, Miller-Cotto, & Ellis, 2023; Schmitt, Purpura, & Elicker, 2019; Willoughby, Wylie, & Little, 2019). However, the nature and the relationship between WM and early math skills remains unclear—specifically, the causal, directional, and dynamic relations among the two skills over time and whether those relations differ across child demographic characteristics. In the current study, we use appropriate statistical methods to extend beyond determining correlations for children at large to consider the co-development and mutual associations between WM and math by determining how these relations differ on the basis of practically meaningful characteristics. Specifically, we consider different levels of family income on the basis of cutoffs used to gate access to federal- and state-funded programs in early childhood in the United States.

Theoretical foundations of WM

WM is a multidimensional construct that supports the temporary storage and manipulation of information during complex cognition. Classic models describe WM as comprising a central executive that coordinates two modality-specific subsystems: a phonological loop for verbal information and a visuospatial sketchpad for visual–spatial information (Baddeley, 2000; Baddeley & Hitch, 1974). Other accounts highlight the role of domain-general attentional control, proposing that WM capacity reflects the ability to maintain task goals and resist interference across modalities (Engle, 2002, 2010). Contemporary developmental work further suggests that these domain-specific and domain-general components coexist along a continuum of control demands (Carretti et al., 2022). Building on this literature, the present study conceptualizes WM as a limited-capacity system encompassing both storage and controlled attention. We simultaneously acknowledge that the measure used in the present study, a backward digit span, primarily taps the verbal/phonological domain and high levels of central-executive control. By situating our work within these complementary frameworks, we treat the observed VWM performance as an index of broader WM capacity, consistent with evidence that verbal tasks with strong executive demands correlate strongly with general WM and predict academic outcomes across content areas (Cornoldi & Giofrè, 2014; Miller-Cotto & Gordon, 2025). However, in recognition of the distinction among different dimensions of WM and potential differential associations (e.g., De Vita, Costa, Tomasetto, & Passolunghi, 2022), we henceforth refer to VWM specifically when discussing the task used in this study.

The role of VWM in mathematics

VWM is related to many other cognitive abilities, including early and elementary mathematics (Diamond, 2013). This may be due to the fact that early math relies heavily on symbolic number representations, sequential processing, and multi-step procedures. Many mathematical tasks require children to retain intermediate values, coordinate rules, and suppress irrelevant information, all of which draw on VWM resources. Indeed, WM generally and VWM specifically are robustly associated with mathematics achievement both concurrently and longitudinally (Byrnes, Wang, & Miller-Cotto, 2019; Peng, Wang, & Namkung, 2018). Meta-analyses have found that the average weighted correlation between WM and math achievement is $r = 0.35$ (Peng et al., 2016, 2018), with a similar degree of association for the relation between mathematics and VWM and visuo-spatial skills (Friso-Van den Bos, Van der Ven, Kroesbergen, & Van Luit, 2013). Further, aspects of children's WM might underlie the ability to more efficiently process information, thus enabling children with higher WM to learn new skills at a more rapid pace than peers with lower WM ability (Case, 1992; Case, Demetriou, Platsidou, & Kazi, 2001; Miller, 1956; Nyikos & Oxford, 1993). Indeed, WM generally and VWM specifically are robust predictors of the growth of mathematical skills over time: Over and above earlier math skills and related abilities, including general intelligence, processing speed, and language skills, WM at school entry predicts mathematical skill development across elementary grades (Blair et al., 2016; McClelland et al., 2014; Ribner et al., 2017; Schmitt, Geldhof, Purpura, Duncan, & McClelland, 2017; Waters, Ahmed, Tang, Morrison, & Davis-Kean, 2021), and beyond (e.g., Coulanges et al., 2021; LeFevre et al., 2013). However, outside of VWM and mathematics skills being correlated, it is unclear how exactly having strong VWM skills supports a child's ability to learn math and how that differs across children. Indeed, despite substantial correlational evidence for both unidirectional and bidirectional support between VWM and math, some have called into question the existence of a causal link (e.g., Willoughby et al., 2019; Willoughby, Kupersmidt, & Voegler-Lee, 2012).

Theoretically, WM may serve as a compensatory capacity for children who start school with low levels of mathematical skills. There is some evidence that WM might disrupt some of the stability in mathematical skills by enabling children to integrate new information more efficiently and effectively (Blair et al., 2016; Ribner et al., 2017) wherein children with higher WM might learn more from the same instructional inputs (Ribner, 2020) and hence make greater than expected gains. That is, children who enter school with relatively lower levels of math knowledge but higher WM capacity than their peers might develop math skills faster, allowing them to catch up to their peers (Blair et al., 2016; Ribner et al., 2017). Indeed, intervention studies have shown that students with higher WM benefit more from specific instructional inputs than do those with lower WM (Swanson, 2014, 2016; Swanson, Orosco, & Reed, 2025). While prior studies have largely used autoregressive approaches to investigate overall patterns across early elementary grades (an inherently difficult-to-interpret analytic approach; see, e.g., Berry & Willoughby, 2017; Hamaker, Kuiper, & Grasman, 2015), relatively few studies have investigated the differential role of WM in mathematics skills for different groups of children despite substantial heterogeneity in both constructs. A better understanding of the effect size of the relation between WM and math and for whom these relations are most apparent may offer insights into who might benefit most from efforts to enhance WM.

Relatively few studies have examined the role of WM and the growth of early math skills (as opposed to math skills at a given point in time), and further, those studies have reported somewhat inconsistent findings. For instance, one study found that executive function—the umbrella term under which WM is broadly subsumed—at age 4 years is correlated with math skills at age 5 years, but not with the growth of math skills from preschool to second grade when accounting for cognitive skills and other metrics of self-regulation (Blair et al., 2015). On the other hand, other work suggests an association of VWM with the slope of math development from kindergarten to second grade (Aunola, Leskinen, Lerkkanen, & Nurmi, 2004; Morgan et al., 2019; Ribner et al., 2023) and from kindergarten through fifth grade (Geary, 2011). More recent work from bilingual-learners in middle elementary grades suggests the same pattern wherein both starting point in WM and growth in WM relate to growth in math skills (e.g., Swanson, Arizmendi, & Li, 2022; Swanson, Kong, & Petcu, 2018). Still, further investigation is needed to elucidate relations between skills over time and across different socioeconomic contexts.

Extant studies which show WM can play a compensatory role in math learning have relied on autoregressive methods and analyzed data from the same cohort (Blair et al., 2016; Ribner et al., 2017). Despite these limitations, the findings highlighted the potential importance of VWM in supporting efficient and effective learning, which may influence the trajectory of mathematical skill development over time. The current study builds on this work by examining whether VWM specifically moderates math development in a way that compensates for lower initial math skills. This investigation employs more robust methodologies and draws on a sample that is larger and more diverse in terms of geography, language, socioeconomic status, and race/ethnicity than those used in previous research.

Socioeconomic status, VWM, and mathematics

While it is increasingly clear that a relation between WM and mathematics exists, examining interaction effects to elucidate individual differences in these relations is needed. Children from low-income homes in the USA often demonstrate poorer WM than peers in higher-income homes (e.g., Raver et al., 2013). However, it is unclear whether the role of VWM in mathematical skill development differs from one group over another. Moreover, research in low-middle income countries has found that children growing up in poverty can have relatively strong WM, comparable to children growing up in higher income countries (Howard et al., 2020); more research is needed to understand cognitive development in adverse conditions (Frankenhuis, Young, & Ellis, 2020; Haslam, Mejia, Thomson, & Betancourt, 2019). This study explores how VWM predicts math differently for children from low- versus higher-income homes in the United States, aiming to understand these relations in various contexts.

Why might the relation between WM and mathematics skills differ by family income? First, differences in resources and the presence of structural and individual biases against lower-income families cannot be overlooked. Second, children growing up in low-income homes tend to enter school with lower levels of mathematics skills than their high-income counterparts. This again may be attributable to differences in access to resources and societal biases, or this may be due to differences in the home math environment (including activities, practices, and language) or parental beliefs (Elliott & Bachman, 2018a, 2018b), or because of individual differences in children's VWM that pre-date kindergarten entry (Bachman et al., 2022). Given that skills like WM affect skill acquisition rates (Blair et al., 2016; Ribner, 2020), poorer WM might contribute to lower rates of math learning. In contrast, better WM might facilitate more efficient math learning (Ribner, 2020). As such, it is also possible that lower performance on WM tasks may be behind some of the lowered performance in math for children from lower-income homes. If these results are obtained, they may support targeted interventions (EF+Math Program, 2021) to promote VWM for children in low-income households or the need to revisit how VWM is assessed for various populations, as has been argued for the broader construct of executive function (Doebel, 2020; Miller-Cotto, Smith, Wang, & Ribner, 2022). Relatedly, since VWM is known to moderate the relationship between various modes of instruction and mathematics skills (Ribner, 2020), these patterns would imply a need for instruction that supports VWM.

The current study

Here, we examined the role of children's family income when examining the relationship between VWM and mathematics in the early grades. We leveraged data from the Early Childhood Longitudinal Study-Kindergarten (ECLS-K) Cohort 2010–11, a nationally representative dataset that includes data for over 18,000 participants with direct assessments of mathematical skills and VWM at each grade from kindergarten to the end of the fifth-grade year. We focused on WM given its strong relation to math (Lee & Bull, 2016) and because of the use of a consistent task across the study—though we are limited to the measurement of VWM specifically given study design. Using these data, we addressed two primary research questions:

1. To what extent do math achievement and VWM at the start of kindergarten predict growth in each skill over elementary grades? To what extent is growth in the VWM and math correlated?

Given prior evidence that executive function—operationalized as a composite whose individual differences are largely attributable to VWM (Ribner et al., 2023)—predicts growth of mathematical skills in early elementary grades, we anticipate we will see a similar pattern of results through fifth grade. Despite theoretical support (cf. Clements, Sarama, & Germeroth, 2016), the empirical evidence for early math supporting the development of executive function or for bidirectional associations is mixed (e.g., Ellis et al., 2021; Schmitt et al., 2017), and one study has in fact reported negative associations between kindergarten math skills and growth in WM (Willoughby et al., 2019). As such, we do not hypothesize a positive association. We treat the relation between growth (i.e., slope) in these two skills as exploratory.

2. To what degree does the magnitude of associations among VWM and mathematics differ depending on students' family income level? In particular, we consider a practically meaningful family income cutoff that represents families' eligibility for priority access to federally funded child care to explore whether the relation between VWM at the start of kindergarten and growth in mathematical skills (and vice versa) is greater for students from low-income versus non-low-income homes.

Our analysis of differential associations among constructs is exploratory. One study which looked at associations among growth in VWM and math skills in a subsample of students who received free−/reduced-price lunch—a proxy that overlaps with but is not fully represented by household income—in a nationally representative population (inclusive of those who receive free−/reduced-price lunch) showed no difference in associations between groups (Willoughby et al., 2019); however, investigating group differences was not a goal of that study and thus the two groups were not directly compared. At the same time, there may be differential exposure to mathematical information for children from lower income homes and WM may affect the ability to catch up as it is associated with the rate of skill acquisition (Blair et al., 2016; Ribner, 2020; Ribner et al., 2023).

Methods

Participants

Participants were recruited for the ECLS-K, a nationally representative sample of 18,174 kindergarteners ($M_{age} = 66.08$ months, SD = 4.64) drawn from 968 schools. Full details of the sampling procedure can be found elsewhere (Tourangeau et al., 2015). Participants (n = 4647) without income information were excluded from the analysis. Thus the analytic sample includes 13,527 (48.6% female) students. Excluded participants were more likely to be white (relative to a race other than white, including more than one race; $\chi^2(1, N = 16{,}847) = 101.99$, $p < .001$) and were slightly younger ($M_{excluded} = 65.95$ months, SD = 4.75; $M_{retained} = 66.12$ months, SD = 4.61; $t(15{,}867) = 2.01$, $p = .044$) than were students retained for analyses.

Procedures

Data for the ECLS-K were collected through primary caregiver interviews and direct child assessment. For this study, assessment data from all available time points were used. All children were assessed in the fall and spring of their kindergarten year (2010–11) and in the spring of each subsequent year (first through fifth grade). A planned missing design was used to assess a representative subset of students in the fall of the first and second-grade years (first-grade $n = 3409$; second-grade $n = 3065$); sampling weights account for missing data. Selection procedures are described elsewhere (Tourangeau et al., 2019). Fall assessments were completed from August through mid-December of each school year, and spring assessments from March through June.

Primary caregiver interview data from the fall of the kindergarten year were used. If child demographic data (e.g., child race, child sex) from the fall interview were unavailable, data from the spring of the kindergarten year were used instead (if present). Data for the ECLS-K are available on the National Center for Education Statistics website at https://nces.ed.gov/ecls/dataproducts.asp#K-5.

Measures

Math skills

The ECLS-K math assessment measured children's problem-solving skills, conceptual understanding, and procedural knowledge. At each assessment timepoint, participants completed a set of routing items which routed them to a second block of low, medium, or high-difficulty items. Item Response Theory (IRT), was used to score assessments so that students across the entire range of ability could be scored on the same metric. The ECLS-K study team computed theta scores to enable modeling change over time; detailed reliability and validity have been reported elsewhere (Tourangeau et al., 2015). Item- and subdomain-level data from the ECLS-K math assessment are not made available by the ECLS-K study team.

Verbal working memory

Participants completed the Numbers Reverse Digit Span (Mather & Schrank, 2001). Children were instructed to verbally repeat an orally presented, increasingly long string of numbers in reverse order. For example, if the child was told the numbers "1…7…3", the correct response would be "3…7…1". Administration ended when a child made three consecutive errors or completed all sequences. An age-standardized *W* score was used. *W* scores are a transformation of an IRT-based Rasch model-computed score designed to provide an interval measure of ability to enable modeling over time (in contrast to an age-normed standardized score). Scores are normed such that the average performance of a child 10 years, 0 months would yield a score of 500 and a standard deviation of 100. *W* scores were obtained using publisher norms for each age point in association with the raw total-correct score for each child.

Family income

Students were categorized as being from "low-income" ($n = 6451$) or "not low-income" ($n = 7070$) homes based on whether their family income fell below or above 200% of the poverty line for a family of a given size. Primary caregivers were asked to report their annual household income and household size. Household size and composition (i.e., number of people over and under age 18 years) corresponded to a federal poverty threshold such that families of a given size whose annual income was under the threshold was considered to be in poverty (e.g., in 2010, the federal poverty threshold for a family of four in the contiguous US was $22,050). Percent of the poverty threshold was calculated by dividing annual household income by the poverty threshold, such that a household with four people with an annual income of $44,000 would be considered just under the cut-off for low income at 199.5% of the federal poverty threshold. As there is no adjustment for location-based cost of living and the federal poverty threshold represents a less-than-living wage for most families, we chose to use 200% of the poverty threshold rather than 100%. Additionally, this 200% cut-off is a meaningful benchmark, as certain government programs (including priority access to federally funded child care slots) is determined on this basis.

Covariates

Covariates were mostly obtained from primary caregiver interviews. Covariates were chosen based on theoretical and empirical relations with children's performance on tests of mathematical and cognitive skills over a school year. Covariates were chosen to estimate the association of key predictor variables with the mathematical skill development.

Primary caregiver interviews

Covariates include indicator variables for child race/ethnicity (white vs. non-white), child sex, and whether the mother was married at the time of child birth. We also include a covariate for children's primary home language. Specifically, parents reported whether the primary home language was English, a language other than English, or two languages equally. This was recoded to indicate whether children were primarily exposed to English in the home (81.6%) or a language other than or in addition to English. Continuous variables included controlling for child age at kindergarten entry and for household size (i.e., number of people in the home under 18 years and number of people 18 years and over). We also controlled for a composite measure of SES created by the ECLS-K study team, comprising occupational prestige, household income, and highest level of education for both parents (if applicable). Occupational prestige was coded from parent-reported occupation using the *Manual for Coding Industries and Occupations* (US Department of Education, National Center for Education Statistics, 1999). Household income was determined from parent interviews. Respondents were asked to choose the range that best reflected their annual household income in $5000 increments from less than $5000 to $75,000, $75,001 to $100,000, $100,001 to $200,000, or greater than $200,000. Highest level of education was reported as the number of years of schooling completed and/or highest degree of schooling sought or completed. This value was then transformed to reflect less than a high school degree, a high school degree or equivalent, vocational/technical training but no diploma, vocational/technical training completion, some college (including associate's degree), college degree, or doctoral or professional degree after college degree. The value of each component for the SES composite was z-scored, and an average of the z-scores was computed.

Direct assessment variables

All analyses control for the IRT scale score from the standardized reading assessment from the fall of the kindergarten year as a control measure for general cognitive ability and understanding of assessment procedures.

Data analysis plan

To examine the relation between VWM and math growth, we first estimate a measurement model for parallel growth in these skills through elementary school. We estimate separate growth trajectories for VWM and math, anticipating non-linear growth over six years and nine data waves from kindergarten to fifth grade (Ahmed, Ellis, Ward, Chaku, & Davis-Kean, 2022; Cameron, Grimm, Steele, Castro-Schilo, & Grissmer, 2015; Ribner et al., 2023). Given the complexity of quadratic terms in parallel process models, we use an unstructured growth term to account for variance in timing and differential loading onto latent slope terms, allowing for non-linear growth.

We then combined these two unstructured growth models into a single parallel process model in which the intercept (starting point) of each skill is allowed to correlate, growth (rate of change) of each skill is allowed to correlate, and growth parameters are regressed on the alternate skill's intercept term. To address our first research question, we then estimated a structural model adjusting for covariates of interest. To address our second question regarding the degree to which the magnitude of associations among constructs differs depending on family income level, we estimated a multi-group model with students split by family income level (low-income vs. non-low-income).

All analyses were run in MPlus 8 (Muthén & Muthén, 2017). Appropriate sampling weights for longitudinal child assessment designed by the ECLS-K study team were applied to re-weight estimates to be nationally representative for all analyses. Additionally, all analyses were adjusted for clustered standard errors at the level of the school in which students were enrolled during the first wave of data collection. Missing data were accounted for using Full Information Maximum Likelihood (FIML) estimation. FIML leverages the covariance matrix for all available data on the independent variables to estimate parameters and standard errors (Enders & Bandalos, 2001).

Transparency and openness

All data are publicly available on the National Center for Educational Statistics Website and can be accessed at https://nces.ed.gov/ecls/dataproducts.asp. Analyses were not preregistered.

Results

Descriptive statistics

Descriptive statistics and bivariate correlations among variables of interest are shown in Table 1. At the bivariate level, the intercepts of math and VWM are highly correlated ($r = 0.83$, $p < .001$), suggesting that, on average, students who start kindergarten with higher levels of one also have higher levels of the other. In contrast, there is a substantially weaker correlation between the rate of growth of both skills ($r = 0.08$, $p = .011$), suggesting development of one may not track development of the other over the course of the elementary grades.

Measurement model

We first estimated a model representing unstructured growth in mathematical skills from the start of kindergarten through the end of fifth grade. This model fit the data well, $\chi^2(33) = 1234.762$, $p < .001$, RMSEA = 0.055 90% CI[0.052,0.057], CFI = 0.954. To confirm this model was better than a linear model with assumptions about data collection intervals, we computed a model with linear growth wherein each measurement occasion $[t+1]$ was set to be 6 months apart (i.e., for third grade and above, $[t+2]$ was used to indicate a 12-month period between measurement occasions). Model fit for the unstructured model was substantially better than for the linear model $\chi^2(40) = 11{,}406.225$, $p < .001$, RMSEA = 0.153 90% CI[0.150, 0.155], CFI = 0.567. A Satorra-Benter Scaled Chi-Squared test revealed that the difference in model fit

Table 1
Descriptive statistics and bivariate correlations for all study variables.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Intercept Working Memory	–												
2	Slope Working Memory	−0.69***	–											
3	Intercept Math	0.83***	−0.51***	–										
4	Slope Math	0.26***	0.08*	0.12***	–									
5	Fall K Reading	0.67***	−0.42***	0.79***	0.02	–								
6	Child Female (vs. Male)	0.05**	−0.04	−0.02	−0.16***	0.06**	–							
7	Child White (vs. non-White)	−0.15***	0.10***	−0.12***	−0.19***	−0.03	0.01	–						
8	Mom Married (vs. Unmarried)	−0.23***	0.12***	−0.24***	−0.18***	−0.22***	−0.02	0.24***	–					
9	Child Age at K Entry	0.20***	−0.20***	0.24***	−0.09***	0.13***	−0.04*	−0.08*	0.01	–				
10	Number of People <18 in Household	−0.09***	0.10***	−0.07***	0.001	−0.10***	−0.01	0.01	−0.06**	0.01	–			
11	Number of People >18 in Household	−0.07**	0.09**	−0.04*	0.02	−0.04	0.01	−0.06*	−0.06*	−0.04	0.08**	–		
12	Family SES	0.40***	−0.24***	0.44***	0.19***	0.40***	0.004	−0.10***	−0.39***	0.02	−0.11***	−0.02	–	
13	Primary Home Language English	0.26***	−0.28***	0.23***	−0.04*	0.18***	−0.01	−0.11***	0.003	0.11***	−0.06***	−0.14***	0.28***	–
	N	12,282	12,282	12,282	12,282	11,787	12,282	12,215	11,967	11,970	10,887	10,887	12,260	12,254
	M	434.65	68.19	36.25	83.34	−1.12	1.48	1.21	1.30	66.24	2.49	2.07	−0.03	0.84
	SD	21.56	15.73	11.41	10.45	0.78	0.50	0.40	0.46	4.76	1.13	0.68	0.78	0.36
	Range	452.96–546.04	−22.15–121.35	−5.32–105.89	27.99–119.35	−3.77–2.99	1–2	1–2	1–2	36.60–88.47	1–13	1–7	−2.33–2.44	0–1

* $p < .05$, ** $p < .01$, *** $p < .001$.

was statistically significant, $\chi^2(7) = 7054.810$, $p < .001$.

Next, we estimated a model representing unstructured growth in VWM. This model also fit the data well, $\chi^2(33) = 296.194$, $p < .001$, RMSEA = 0.026 90% CI[0.023,0.028], CFI = 0.974 and better than a model with linear growth, $\chi^2(40) = 2455.693$, $p < .0001$, RMSEA = 0.070 90% CI[0.068,0.073], CFI = 0.764. A Satorra-Benter Scaled Chi-Squared test revealed that the difference in model fit was statistically significant, $\chi^2(7) = 1942.805$, $p < .001$.

Finally, we estimated a parallel process model using the unstructured growth terms from the well-fitting models for math and VWM. The resulting model fit the data well, $\chi^2(143) = 1957.484$, $p < .001$, RMSEA = 0.032 90% CI[0.031,0.034], CFI = 0.957. Means, intercepts, and variances of each parameter were statistically significant, indicating that terms differed significantly from zero and that inter-individual variability existed in the starting point and rate of change. The model is depicted visually in Fig. 1.

Structural model

We adjusted for a series of covariates using the parallel process model estimated above. The model fit the data well with covariate adjustment, $\chi^2(269) = 2295.256$, $p < .001$, RMSEA = 0.025 90% CI [0.024,0.026], CFI = 0.955. Results are shown in Table 2. Intercepts of math and VWM were strongly correlated with one another $\beta = 0.63$, $p < .001$, and slopes were moderately correlated, $\beta = 0.29$, $p < .001$. This result suggests that students who begin school with relatively high levels of mathematics skills tend to also begin school with relatively high levels of VWM (and vice versa). Over and above starting points, the development of skills over time is also related, such that growth in one skill is typically accompanied by growth in the other.

Within-skill growth was negatively associated with the starting point for both math and VWM. VWM intercept and slope were strongly negatively correlated ($\beta = -0.43$, $p < .001$). Math intercept and slope showed the same pattern but to a lesser degree ($\beta = -0.08$, $p = .001$). This pattern of results might reflect the non-linear nature of the development of both skills (whereby the rate of skill development decreases over time as skills assessed become more difficult) or might indicate a ceiling effect for assessment of these skills; that is, those who begin with stronger skills have less room for improvement.

Interestingly, directional associations between the constructs are seemingly at odds. The intercept of VWM is positively associated with the growth rate in math, $\beta = 0.43$, $p < .001$; however, the intercept of math is *negatively* associated with the growth rate in VWM, $\beta = -0.42$, $p < .001$. That is, students who begin school with higher levels of VWM are more likely to develop mathematical skills faster than those with lower levels of VWM. In contrast, students who begin school with high levels of math may develop VWM skills at a slower rate than their peers who begin school with lower levels of mathematical skill.

Multi-group model

Finally, we estimated a multi-group model. The same structural model was simultaneously estimated for students from low-income and non-low-income households to test whether the relative associations between VWM and math differed by group. The resulting overall model fit the data well, $\chi^2(538) = 2730.67$, $p < .001$, RMSEA = 0.026 90% CI [0.025,0.027], CFI = 0.949. Results are shown in Table 3. As anticipated, parameters differed between groups, suggesting that VWM and math are differentially associated among children from low-income vs. non-low-income households. Multigroup models are depicted visually in

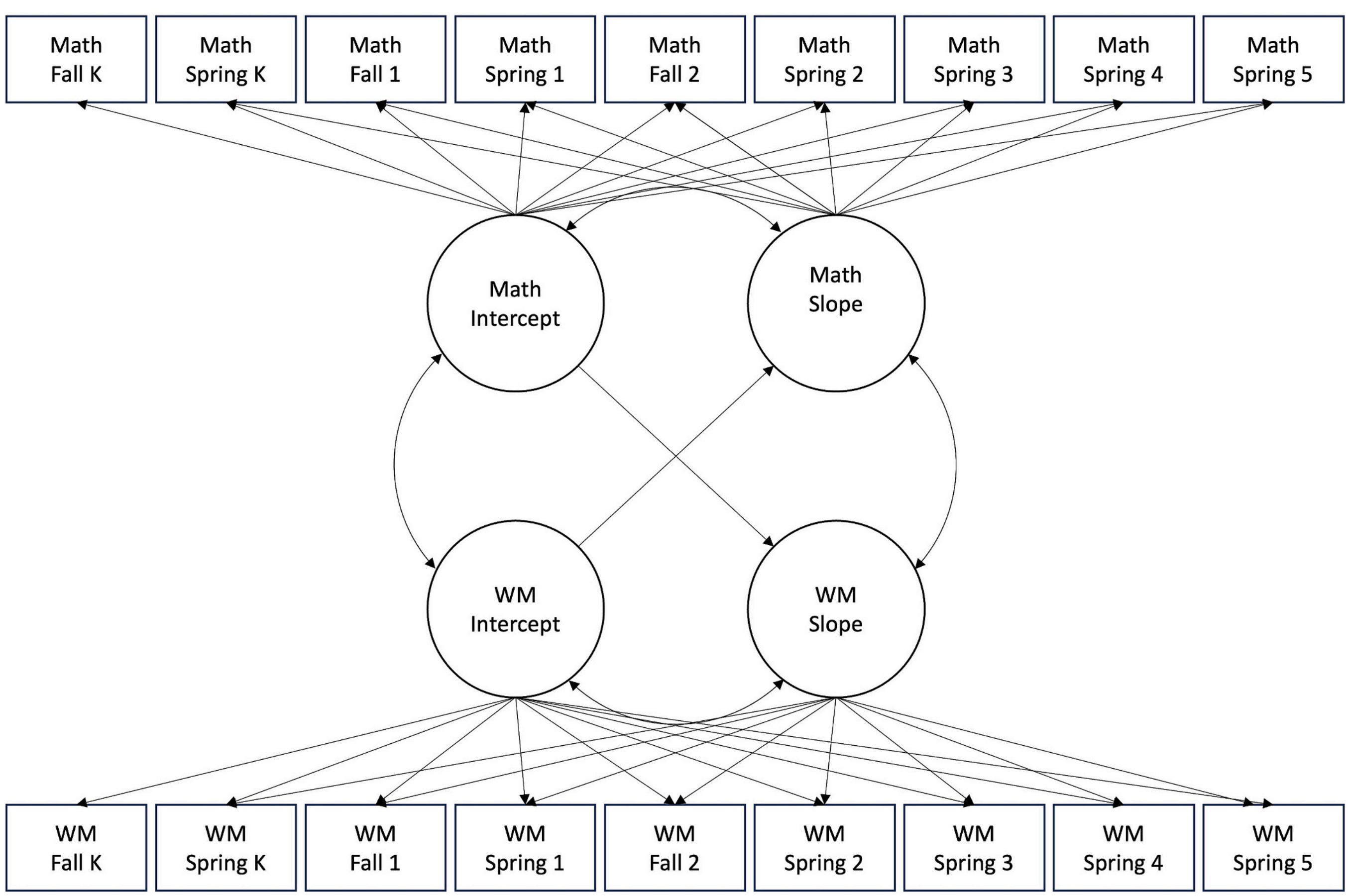

Fig. 1. Parallel process model depicting correlated intercepts and slopes of math and WM from kindergarten to 5th grade.
All pathways, means, and variances are statistically significant at $p < .001$. Factor loadings and values are not shown for simplicity.

Table 2
Results of structural parallel process model.

		Beta	SE	*p*-value
Intercept Math	Fall Kindergarten Reading	0.72	0.01	< 0.001
	Child Female (vs. Male)	−0.05	0.01	< 0.001
	Child White (vs. non-White)	−0.07	0.01	< 0.001
	Mom Married (vs. Unmarried)	−0.01	0.01	0.359
	Child Age at Kindergarten Entry	0.14	0.01	< 0.001
	Number of People <18 in Household	0.02	0.01	0.158
	Number of People ≥18 in Household	−0.01	0.01	0.407
	Family Socioeconomic Status Composite	0.14	0.01	< 0.001
	Primary Home Language English	0.01	0.01	0.295
Intercept VWM	Fall Kindergarten Reading	0.58	0.02	< 0.001
	Child Female (vs. Male)	0.03	0.02	0.114
	Child White (vs. non-White)	−0.10	0.02	< 0.001
	Mom Married (vs. Unmarried)	−0.03	0.02	0.125
	Child Age at Kindergarten Entry	0.10	0.02	< 0.001
	Number of People <18 in Household	−0.01	0.02	0.749
	Number of People ≥18 in Household	−0.03	0.02	0.104
	Family Socioeconomic Status Composite	0.12	0.02	< 0.001
	Primary Home Language English	0.08	0.02	< 0.001
Slope Math	Fall Kindergarten Reading	−0.29	0.03	< 0.001
	Child Female (vs. Male)	−0.17	0.02	< 0.001
	Child White (vs. non-White)	−0.12	0.02	< 0.001
	Mom Married (vs. Unmarried)	−0.07	0.03	0.005
	Child Age at Kindergarten Entry	−0.14	0.02	< 0.001
	Number of People <18 in Household	0.01	0.02	0.716
	Number of People ≥18 in Household	0.01	0.02	0.816
	Family Socioeconomic Status Composite	0.14	0.02	< 0.001
	Primary Home Language English	−0.12	0.02	< 0.001
	Working Memory Intercept	**0.43**	**0.04**	**< 0.001**
Slope VWM	Fall Kindergarten Reading	−0.04	0.04	0.275
	Child Female (vs. Male)	−0.05	0.02	0.019
	Child White (vs. non-White)	0.05	0.03	0.035
	Mom Married (vs. Unmarried)	0.01	0.03	0.804
	Child Age at Kindergarten Entry	−0.07	0.02	0.003
	Number of People <18 in Household	0.05	0.02	0.048
	Number of People ≥18 in Household	0.04	0.03	0.113
	Family Socioeconomic Status Composite	0.03	0.03	0.375
	Primary Home Language English	−0.16	0.02	< 0.001
	Math Intercept	**−0.42**	**0.04**	**< 0.001**

Fig. 2.

As in the average structural model above, math and VWM intercepts were strongly correlated (low-income: $\beta = 0.69$, $p < .001$; non-low-income: $\beta = 0.60$, $p < .001$), and a Wald test of parameter constraints confirmed that values were not significantly different from one another $\chi^2(1) = 2.71$, $p = .100$. In contrast, slope terms were more strongly related for children from low-income households ($\beta = 0.38$, $p < .001$) than for those from non-low-income households ($\beta = 0.22$, $p < .001$); these values differed from one another, $\chi^2(1) = 9.40$, $p = .002$.

The within-construct association between the starting point and growth rate for math and VWM did not differ between the two groups. For students from low-income households, the association between the intercept and slope for math was non-significant, $\beta = -0.01$, $p = .752$; the association for students from non-low-income homes was statistically significant, though relatively small, $\beta = -0.11$, $p = .001$, and the parameters were not meaningfully different from one another, $\chi^2(1) = 2.74$, $p = .098$. Similarly, the associations between intercept and slope of VWM were similar between groups (low-income: $\beta = -0.38$, $p < .001$; non-low-income: $\beta = -0.45$, $p = .001$) with no difference between groups: $\chi^2(1) = 0.10$, $p = .755$.

We next examined the association between the intercept of each construct and the slope of the other. As with the overall structural model presented above, the starting point of math was negatively associated with the growth rate in VWM (low-income: $\beta = -0.44$, $p < .001$; non-low-income: $\beta = -0.38$, $p = .001$). Parameters did not differ across groups; $\chi^2(1) = 1.40$, $p = .236$. In contrast, we find that the starting point of VWM is nearly twice as predictive of the growth rate in math for children from low-income households ($\beta = 0.48$, $p < .001$) than for those from non-low-income households ($\beta = 0.29$, $p < .001$). These parameters were significantly different, $\chi^2(1) = 9.51$, $p = .002$, suggesting VWM might be particularly important for the growth rate in math in children from low-income homes. This result is depicted using model-estimated means in Fig. 3.

Discussion

This study examined how VWM predicts math differently for children from low vs. non-low-income homes using nationally representative data for elementary grade students in the United States. We found that students beginning school with higher levels of VWM were more likely to develop mathematical skills faster than those with lower levels of VWM. Notably, the starting point of VWM was nearly twice as predictive of growth in math skills for children from low-income households as for children from higher-income households. Children with higher VWM performance may better attend to classroom information, aiding in math skill acquisition, especially for those from low-income backgrounds who may lack such opportunities at home (Finch, 2019). This finding suggests that VWM is related to math growth (Coolen et al., 2021; Miller-Cotto & Byrnes, 2020; Schmitt et al., 2017). Second, children from low-income homes may use VWM as a mechanism to facilitate learning (Miller-Cotto & Byrnes, 2020; Zhang & Peng, 2023) to compensate for a lack of early math skills. However, the causal mechanisms explaining why VWM supports early math are unclear, suggesting a need for more explicit theories of change (Scerif et al., 2023).

Our results revealed that mathematics' starting point and growth rate were negatively correlated, and to a lesser degree than VWM's starting point and growth rate. Interestingly, and in contrast to the positive association between VWM's starting point and growth in math, we see a negative association between math's starting point and growth in VWM. Each of these might reflect the non-linear nature of the development of both skills or indicate a ceiling effect for assessing these skills given the constraints of the task (the VWM task notably being the same task used over time whereas the math task is adjusted to each assessment to scale to children's knowledge and abilities). Finally, another interpretation is that non-low-income students with low VWM are buffered from the effects of low VWM by other factors (e.g., better teachers and access to tutoring/remediation). Therefore, helping students from low-income homes with lower VWM by providing them with similar supports as exist in schools typically attended by higher-income peers may also be effective, and identifying students with lower VWM for extra support could be more beneficial than supporting everyone (including those with higher VWM who may catch up anyway). Further research is

Table 3
Results of multi-group parallel process model.

		Non-Low-Income			Low-Income		
		Beta	SE	p-value	Beta	SE	p-value
Intercept Math	Fall Kindergarten Reading	0.72	0.01	< 0.001	0.73	0.02	< 0.001
	Child Female (vs. Male)	−0.05	0.01	< 0.001	−0.05	0.02	0.015
	Child White (vs. non-White)	−0.05	0.02	0.002	−0.08	0.02	< 0.001
	Mom Married (vs. Unmarried)	−0.04	0.02	0.017	0.02	0.02	0.468
	Child Age at Kindergarten Entry	0.15	0.02	< 0.001	0.15	0.02	< 0.001
	Number of People <18 in Household	0.04	0.01	0.003	0.00	0.02	0.982
	Number of People ≥18 in Household	−0.01	0.01	0.481	−0.01	0.02	0.613
	Family Socioeconomic Status Composite	0.08	0.01	< 0.001	0.12	0.02	< 0.001
	Primary Home Language English	0.03	0.01	0.082	0.00	0.02	0.969
Intercept VWM	Fall Kindergarten Reading	0.60	0.02	< 0.001	0.58	0.03	< 0.001
	Child Female (vs. Male)	0.05	0.02	0.022	0.01	0.03	0.785
	Child White (vs. non-White)	−0.08	0.02	0.001	−0.12	0.03	< 0.001
	Mom Married (vs. Unmarried)	−0.06	0.03	0.028	−0.01	0.03	0.865
	Child Age at Kindergarten Entry	0.09	0.02	< 0.001	0.12	0.03	< 0.001
	Number of People <18 in Household	0.03	0.02	0.161	−0.03	0.03	0.270
	Number of People ≥18 in Household	−0.02	0.03	0.539	−0.05	0.03	0.099
	Family Socioeconomic Status Composite	0.05	0.02	0.021	0.14	0.03	< 0.001
	Primary Home Language English	0.07	0.02	0.001	0.06	0.03	0.027
Slope Math	Fall Kindergarten Reading	−0.36	0.04	< 0.001	−0.18	0.04	< 0.001
	Child Female (vs. Male)	−0.16	0.02	< 0.001	−0.18	0.03	< 0.001
	Child White (vs. non-White)	−0.08	0.03	0.014	−0.14	0.03	< 0.001
	Mom Married (vs. Unmarried)	−0.04	0.03	0.150	−0.07	0.04	0.048
	Child Age at Kindergarten Entry	−0.17	0.03	< 0.001	−0.11	0.03	< 0.001
	Number of People <18 in Household	0.02	0.02	0.411	0.02	0.03	0.554
	Number of People >18 in Household	−0.01	0.03	0.727	0.00	0.03	0.952
	Family Socioeconomic Status Composite	0.12	0.03	< 0.001	0.10	0.03	0.001
	Primary Home Language English	−0.09	0.03	0.003	−0.16	0.04	< 0.001
	Working Memory Intercept	0.29	0.05	< 0.001	0.48	0.05	< 0.001
Slope VWM	Fall Kindergarten Reading	−0.10	0.05	0.039	0.03	0.06	0.655
	Child Female (vs. Male)	−0.07	0.03	0.025	−0.04	0.04	0.256
	Child White (vs. non-White)	0.10	0.03	0.002	0.03	0.04	0.537
	Mom Married (vs. Unmarried)	0.02	0.03	0.646	0.00	0.04	0.917
	Child Age at Kindergarten Entry	−0.06	0.03	0.053	−0.09	0.04	0.020
	Number of People <18 in Household	0.04	0.03	0.242	0.06	0.03	0.079
	Number of People >18 in Household	0.00	0.03	0.956	0.06	0.04	0.101
	Family Socioeconomic Status Composite	0.06	0.03	0.053	−0.06	0.04	0.132
	Primary Home Language English	−0.08	0.03	0.007	−0.19	0.04	< 0.001
	Math Intercept	−0.38	0.05	< 0.001	−0.44	0.07	< 0.001

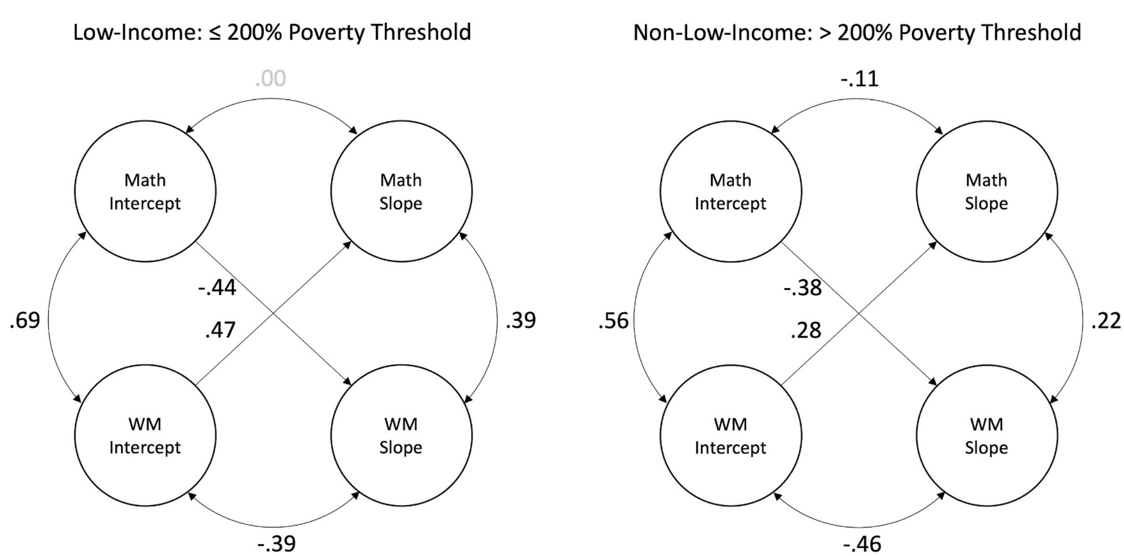

Fig. 2. Multigroup parallel process models with intercepts of math and working memory predicting growth in the alternate skill.
All parameters in black represent standardized beta values and are statistically significant at $p \leq .001$. Covariates and manifest variables not depicted for simplicity and interpretability. Covariates include child reading skills at the start of kindergarten, child sex, child race (white vs. non-white), child age at kindergarten entry, family size, family socioeconomic status composite, and whether or not the mother is married.

needed to better understand whether these seemingly counterintuitive associations persist across assessments and contexts.

This study and previous research suggest strong VWM compensates for lower prior math knowledge, while students with strong math skills

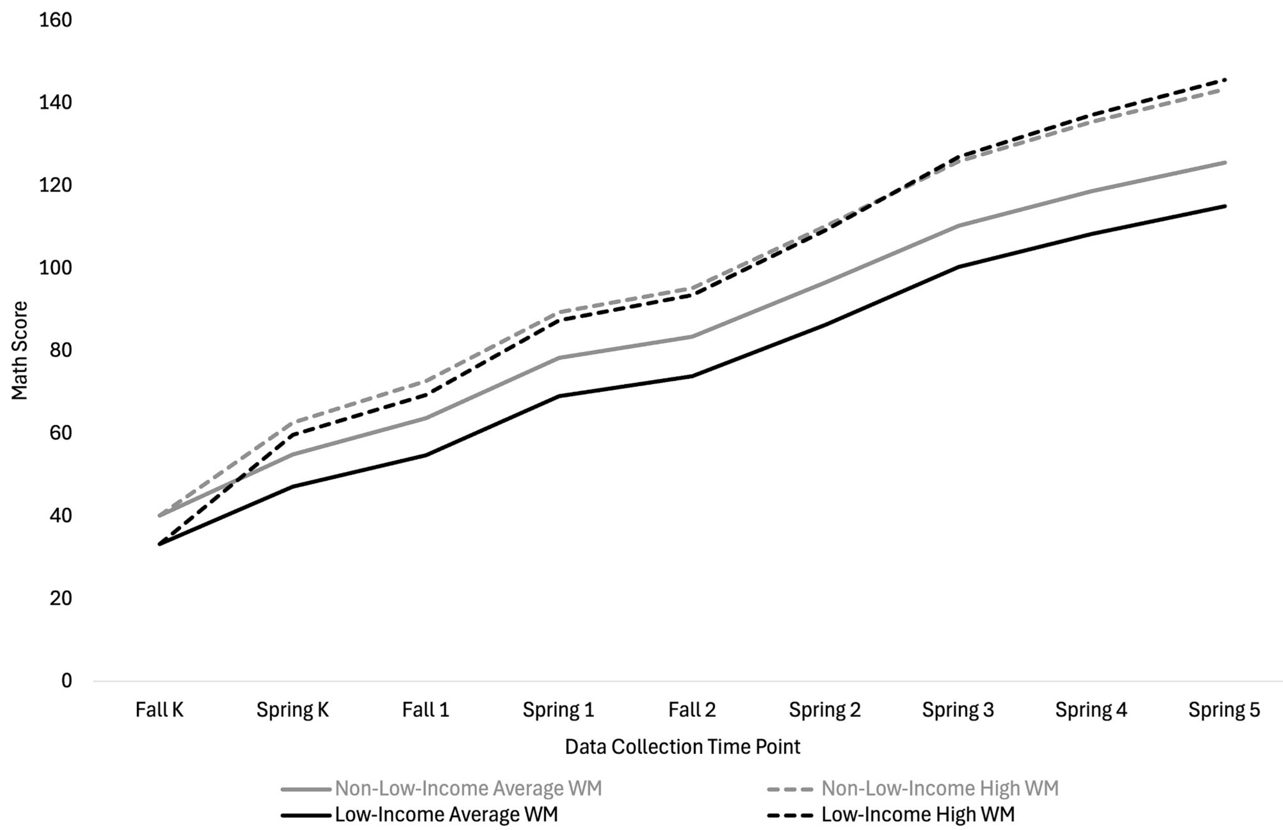

Fig. 3. Hypothetical growth curves using model-estimated means and slope parameters for children from low-income and non-low-income homes. Solid bars represent model-estimated means for each group. Dashed lines represent growth attributable to high WM, computed as 1SD above the mean.

rely less on VWM (Ribner, 2020; Zhang & Peng, 2023). This relation is stronger for children from low-income homes, who often demonstrate lower VWM due to structural inequities (Gaskins & Alcalá, 2023; Miller-Cotto et al., 2022). While the mechanism underlying this association remains unclear, it may be due to individual differences in how children attend to, integrate, and act upon instruction in the classroom (Ribner, 2020). More work is needed to examine these mechanisms. Still, this adds to the evidence that supporting early VWM in a mathematical context may accelerate learning. Future research should test if VWM training within the context of mathematical learning is more effective for enhancing VWM than VWM or math training alone, though current VWM training is generally ineffective (Diamond & Ling, 2018; Kassai, Futo, Demetrovics, & Takacs, 2019). Instead, we may focus on holistic environmental factors by supporting low-income families to prevent these differences in the first place (Niebaum & Munakata, 2023; Scerif et al., 2023).

Few frameworks of WM explicitly consider how socioeconomic context shapes WM development or its role in academic learning. We adopt a modality-independent perspective (Engle, 2002, 2010), which emphasizes controlled attention across modalities and aligns with our use of a VWM measure as an index of goal maintenance and interference control. At the same time, we recognize evidence for multi-component and continuum models that distinguish verbal, visual, and spatial resources and levels of executive control (Cornoldi & Giofrè, 2014). Our results advance this literature by demonstrating that VWM serves a compensatory function for children from low-income backgrounds, a relationship not well articulated in existing WM theories or socioeconomic frameworks. This may help to bridge the gap between research on cognitive processes and frameworks of socioeconomic risk, highlighting the need for theories that integrate both individual cognitive capacities and structural inequalities.

Our findings underscore several actionable avenues for educational practice and policy, particularly for children from low-income families. Because VWM at school entry was nearly twice as predictive of math growth for children in low-income households relative to more advantaged peers, school may incorporate VWM-supportive instructional strategies, such as guided practice with scaffolds, opportunities for verbal rehearsal, and structured problem-solving routines within mathematics lessons. At the policy level, these results highlight the importance of expanding access to federally funded early learning initiatives (e.g., Head Start, state funded pre-k) and professional development that trains educators to integrate VWM supports into math instruction. These efforts may help narrow opportunity gaps by bolstering cognitive resources that facilitate math learning and strong VWM-supported instruction.

This study has several strengths. The large sample size provides a nationally representative sample in the United States, enhancing generalizability and enabling comparisons between children from low- and non-low-income homes. Appropriate statistical analyses were also applied to this large longitudinal sample (Hamaker et al., 2015), enabling us to track growth rates of multiple skills across multiple grades from school entry. However, the study is limited by the WM measures used in ECLS-K, specifically the narrow but reliable and widely used Number Reversed task involving VWM with a numerical component (i.e., repeating the names of numbers). The observed relations might differ with other WM or executive function components. Studies indicate that other specific components of executive function, like inhibitory control, are particularly important for certain mathematical domains, such as rational numbers (Abreu-Mendoza, Coulanges, Ali, Powell, & Rosenberg-Lee, 2020; Leib et al., 2023). This ECLS-K cohort also uses a broad measure of math achievement, and WM components may relate differently to various math skills, like computation versus applied problem-solving. Future research should examine individual math skills (e.g., patterning, arithmetic, number sense) to better understand these relationships. Another consideration is how we define income and the distinction between high and low-income households. We classified households as “low-income” or “non low-income” based on whether family income fell below or above 200% of the poverty line, which may not capture nuances like family size, cost of living, and access to opportunities, nor may it effectively represent the dynamic nature of income over time, particularly among low-income families who may see greater fluctuation in their income month-to-month or year-to-year. Further, we acknowledge that there is greater diversity within these groups that our analyses do not appropriately account for, potentially requiring more person-centered approaches to describe this nuance. Relatedly, more informative approaches may involve creating a latent “proximity to opportunity” variable encompassing income, needs, access to resources, and factors like maternal education to better capture the impacts of SES on children's skill acquisition (Antonoplis, 2023) and/or separately estimating the relative contribution of different SES components to better understand targets of policy-relevant intervention (Schneider, Behboudi, & Maguire, 2024). However, despite this rather coarse metric, this cutoff remains practically meaningful, as several means-tested programs, including priority access to federally funded child care, are determined at the level of 200% of the federal poverty threshold and eligibility for others (e.g., Medicaid, SNAP, WIC) fall between 100 and 200% (at the time of data collection). As effective intervention might be enacted through federally funded child care (e.g., Head Start), considering differential associations for children who qualify for access versus those who do not may be financially expedient.

Finally, despite the longitudinal nature of these data and the patterns of growth implied by analytic techniques, neither directionality nor causality can be inferred. Growth in both VWM and math may be due to an unmeasured variable, including characteristics of classrooms, homes, or out-of-school contexts; however, by controlling for intercept and slope of each skill, we can minimize—though not eliminate—this concern. This includes a more in-depth consideration of language and literacy skills; though we include kindergarten entry reading skills as a covariate in analyses, this does not represent the nuanced skills that comprise language and literacy development. Furthermore, the developmental trajectories of math and reading in elementary grades differ (e.g., Little, Lonigan, & Phillips, 2021) and there may be implications for not only the starting point but also the growth in reading skills over time. Furthermore, and as noted above, we remain uncertain about the causal nature of these relations. Little evidence suggests that intervening directly on VWM or mathematics has a meaningful effect on the other (Cao, Huang, Huang, Xie, & Wang, 2020; Kassai et al., 2019; Melby-Lervåg & Hulme, 2013). Further study of the mechanisms underlying relations between WM and math—and specific subdomains of both math and WM given the multidimensional nature of each—is needed before we can comfortably call for a contextual intervention on one skill or another. Finally, we must acknowledge the unique context in which these data were collected. Despite data being drawn from a nationally representative sample who represent geographic, racial, ethnic, linguistic, and socioeconomic diversity in the United States, data are rooted in a particular time (2010–2016): Children were in kindergarten shortly after the financial crisis that began in 2008 and in fifth grade not long before the COVID-19 pandemic began in 2020, two massive macroeconomic events. It may be that these results are not generalizable to other points in sociohistorical time.

Nevertheless, an important takeaway from this study is that asking *what* works when determining the relationships between constructs is not enough. Still, we should also ask *how* it works and *for whom* when designing interventions. VWM may serve as a compensatory mechanism for children from low-income homes who have not had the opportunity to learn mathematics content before beginning formal schooling. Indeed, to be clear, the differences in VWM or math skills are due to differences in opportunities systematically unavailable to low-income communities and families. Supporting the opportunities to develop strong VWM through household resources, learning strategies, or classroom materials that support VWM ability may benefit children at risk for poor math skills. More importantly, we must consider practical ways to support children and low-income families to prevent these differences in the first place.

AI declaration

No AI tools, including generative AI, were used in any stage of the preparation of this manuscript.

CRediT authorship contribution statement

Andrew D. Ribner: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Dana Miller-Cotto:** Writing – review & editing, Writing – original draft, Conceptualization. **Rebecca Merkley:** Writing – review & editing, Writing – original draft, Conceptualization. **Luis M. Rivera:** Writing – review & editing, Conceptualization. **Miriam Rosenberg-Lee:** Writing – review & editing, Conceptualization.

Declaration of competing interest

None.

Data availability

Data are publicly available and accessible at https://nces.ed.gov/ecls/dataproducts.asp#K-5

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