Received: 30 November 2018 | Revised: 12 August 2019 | Accepted: 3 December 2019

DOI: 10.1111/desc.12937

PAPER

Developmental Science WILEY

Individual differences in executive function partially explain the socioeconomic gradient in middle-school academic achievement

W. Dustin Albert[1] | Jamie L. Hanson[2] | Ann T. Skinner[3] | Kenneth A. Dodge[3] | Laurence Steinberg[4] | Kirby Deater-Deckard[5] | Marc H. Bornstein[6,7] | Jennifer E. Lansford[3]

[1]Bryn Mawr College, Philadelphia, PA, USA

[2]University of Pittsburgh, Pittsburgh, PA, USA

[3]Center for Child and Family Policy, Duke University, Durham, NC, USA

[4]Temple University, Philadelphia, PA, USA

[5]University of Massachusetts at Amherst, Amherst, MA, USA

[6]Eunice Kennedy Shriver National Institute of Child Health and Human Development, Bethesda, MD, USA

[7]Institute for Fiscal Studies, London, UK

Correspondence
W. Dustin Albert, 101 N Merion Ave, Bryn Mawr, PA 19010, USA.
Email: walbert@brynmawr.edu

Funding information
International Research Fellowship in collaboration with the Centre for the Evaluation of Development Policies (EDePO) at the Institute for Fiscal Studies (IFS), London, UK, funded by the European Research Council (ERC) under the Horizon 2020 research and innovation programme, Grant/Award Number: 695300-HKADeC-ERC-2015-AdG; Eunice Kennedy Shriver National Institute of Child Health and Human Development, Grant/Award Number: RO1-HD054805; Intramural Research Program of the NIH/NICHD, USA; The research was supported in part by grant P30DA023026 from the National Institute on Drug Abuse

Abstract

Children from families with low socioeconomic status (SES) earn lower grades, perform worse on achievement tests, and attain less education on average than their peers from higher-SES families. We evaluated neurocognitive mediators of SES disparities in achievement in a diverse sample of youth whose data were linked to administrative records of performance on school-administered tests of 7th grade reading and math proficiency (N = 203). We used structural equation modeling to evaluate whether associations between SES (measured at ages 8–9) and achievement (measured at age 13) are mediated by verbal ability and executive function (measured at age 10), a suite of top-down mental processes that facilitate control of thinking and behavior. Children from relatively higher-SES families performed better than their lower-SES peers on all neurocognitive and achievement measures, and SES disparities in both reading and math achievement were partially mediated by variation in executive function, but not verbal ability. SES disparities in executive function explained approximately 37% of the SES gap in math achievement and 17% of the SES gap in reading achievement. Exploratory modeling suggests that SES-related variation in working memory may play a particularly prominent role in mediation. We discuss potential implications of these findings for research, intervention programming, and classroom practice.

KEYWORDS

academic achievement, executive function, socioeconomic status, working memory

1 | INTRODUCTION

Children born into families on the lower rungs of the socioeconomic ladder confront poor odds of substantially improving their socioeconomic status as adults (Lee & Solon, 2009). One important mechanism contributing to this lack of social mobility is the socioeconomic gap in academic achievement (Brooks-Gunn & Duncan, 1997). On average, children from families with relatively low socioeconomic status (SES), typically indexed by parental education and income, earn lower grades, perform worse on standardized achievement tests, and attain less education than their higher-SES peers (Bradley & Corwyn, 2002; Haveman & Wolfe,

1995). Associations between SES and academic achievement persist throughout childhood and adolescence and are evident across the full socioeconomic spectrum (Reardon, In, & York, 2011). Furthermore, at least a portion of the SES-achievement gap is attributable to causal effects of family income: For instance, studies estimating the impact of anti-poverty policy interventions like the Earned Income Tax Credit have identified positive impacts of increased family income on child achievement (Dahl & Lochner, 2012). In the absence of comprehensive policy reforms to reduce income inequality at the societal level, the burden of addressing SES disparities in academic achievement will fall largely on educators and interventionists. In addition to providing support services addressing the nutritional and mental health challenges frequently faced by students from low-income families, stakeholders might consider changes to curricular or instructional practices to help address the most common cognitive barriers to learning faced by disadvantaged students. To help target these efforts, research is needed to identify specific domains of cognitive functioning that best account for the SES gradient in academic achievement. This study contributes to this effort by evaluating the degree to which executive function and verbal ability mediate the association between childhood SES and academic achievement across the transition to middle school.

Research Highlights

- We evaluated neurocognitive mediators of socioeconomic disparities in performance on school-administered tests of 7th grade reading and math proficiency.
- Children from relatively higher-SES families performed better than their lower-SES peers on all neurocognitive and achievement measures.
- SES disparities in both reading and math achievement were partially mediated by variation in executive function, but not verbal ability.
- Exploratory modeling suggests that SES-related variation in working memory may play a particularly prominent role in mediation.

1.1 | Socioeconomic gradients in cognitive development

To date, much of the research on mechanisms underlying the SES-achievement gap has focused on qualities of the child's environment that vary along the SES gradient and are likely to shape cognitive development. Children from lower-SES families are more likely than their peers to be exposed to a variety of stressors, including (but not limited to) family turmoil and instability, violence in the home and neighborhood, and environmental toxins (Evans, 2004). At the same time, they may experience less responsive parenting and social support and may be exposed to fewer cognitively stimulating materials and experiences in both home and school environments (Bradley & Corwyn, 2002). Collectively, this work underscores the degree to which research on SES gradients in developmental outcomes inherently capitalizes on the capacity of SES to serve as a proxy measure of a child's cumulative exposure to a broad array of positive and negative experiences known to powerfully shape physical, socioemotional, and cognitive development.

Although SES is a well-established predictor of performance on broad measures of cognitive ability (e.g., fluid intelligence; Duyme, Dumaret, & Tomkiewicz, 1999; Gottfried et al., 2003), more recent research has begun to map SES-cognition associations at a much finer level of analysis by employing modern neuropsychological assessments. Because neuropsychological tests were initially developed to characterize the (often subtle) cognitive and behavioral consequences of localized brain lesions (Heaton & Pendleton, 1981), they are capable of indexing individual differences in well-defined neurocognitive functions associated with the integrity of specific neural systems. A growing body of neuropsychological research points to SES disparities in executive function (EF), a subset of neurocognitive capacities related to top-down control of attention and behavior (e.g., Farah et al., 2006; Last, Lawson, Breiner, Steinberg, & Farah, 2018; Mezzacappa, 2004; Noble, McCandliss, & Farah, 2007; Waber et al., 2007). There is broad consensus that the protracted maturation of the prefrontal cortex (PFC) and its reciprocal connections to other brain regions contribute to the relatively late maturation of EF capacities (Casey, Getz, & Galvan, 2008; Luna, Padmanabhan, & O'Hearn, 2010), which in some cases show efficiency gains into the twenties (Albert & Steinberg, 2011). Farah and colleagues have argued that this protracted maturational timetable may render EF development particularly vulnerable to disruption by the cumulative stresses associated with childhood socioeconomic deprivation (Hackman, Farah, & Meaney, 2010). A meta-analysis of studies reporting correlations between childhood SES and EF in samples ranging in age from 2 to 18 years identified small but statistically significant correlations between SES and working memory (r = .18), attention shifting (r = .17), and response inhibition (r = .14) (G. Lawson, Hook, & Farah, 2017).

SES is also consistently associated with variation in verbal ability (Hoff, 2003; Hoff & Tian, 2005; Mercy & Steelman, 1982; Nittrouer, 1996; Noble et al., 2007). Noble et al. (2007) evaluated SES differences in performance on a broad array of neurocognitive tasks and found the largest effects on measures of verbal ability, alongside smaller but significant effects on measures of EF. SES disparities in verbal ability are also observed longitudinally. For instance, among children born to participants of the National Longitudinal Survey of Youth 1979, a nationally representative cohort study, large differences in vocabulary knowledge between low- and high-SES strata were already apparent by age 3 and persisted through age 13 (Farkas & Beron, 2004). These findings are consistent with observations that children from lower-SES homes may be exposed to a much more limited vocabulary in the home environment relative to their higher-SES peers (Hart & Risley, 2003).

1.2 | Neurocognitive foundations of academic achievement

The domains of neurocognitive functioning with the strongest associations with SES—namely, executive function and verbal ability—are also important predictors of academic achievement, independent of SES. Much of the work on EF has focused on its role as a foundation for early childhood school readiness (Blair & Razza, 2007; Bull, Espy, & Wiebe, 2008). Studies have also demonstrated correlations between EF and childhood and adolescent performance on standardized tests of math and reading achievement, measured concurrently (e.g., Best, Miller, & Naglieri, 2011; St Clair-Thompson & Gathercole, 2006) and, in fewer cases, prospectively (Mazzocco & Kover, 2007; Welsh, Nix, Blair, Bierman, & Nelson, 2010). However, the literature on EF and academic achievement is not entirely consistent; some studies have found significant associations between EF and math but not EF and reading (Brock, Rimm-Kaufman, Nathanson, & Grimm, 2009; Schmitt, McClelland, Tominey, & Acock, 2015).

In addition to EF, verbal ability is one of the most consistent predictors of academic achievement (Duncan et al., 2007). Specifically, verbal skills measured around the time of school entry are associated with math and reading achievement across the elementary school years (Beron & Farkas, 2004; Kurdek & Sinclair, 2001; Lonigan, Burgess, & Anthony, 2000).

1.3 | Neurocognitive mediators of the SES-achievement gap

Despite substantial research identifying associations between SES and neurocognitive functioning, and between neurocognitive functioning and academic achievement, few studies have formally evaluated the degree to which individual differences in neurocognitive functioning account for the SES gradient in achievement. Most have been conducted with young children and focused on the role of EF. For instance, research on mechanisms underlying the association between SES and school readiness among preschool children identified mediating roles for attention and inhibitory control (NICHD Early Child Care Research Network, 2003) as well as latent or composite measures of EF (Dilworth-Bart, 2012; Fitzpatrick, McKinnon, Blair, & Willoughby, 2014). Likewise, a study of elementary school children showed that associations between early childhood SES and first grade math and literacy scores are mediated by a latent variable estimate of EF (but not expressive vocabulary) derived from tasks administered in kindergarten (Nesbitt, Baker-Ward, & Willoughby, 2013). Crook and Evans (2014) found that associations between childhood SES and fifth grade math and reading scores are mediated by planning skills, measured in the third grade using the Tower of Hanoi task.

Evidence also exists supporting the mediating role of verbal ability. Beron and Farkas (2004) found support for the role of verbal ability as a mediator of SES differences in reading achievement among a large sample of elementary school children, although the study did not control for differences in EF. Fitzpatrick et al. (2014) accounted for the unique contributions of EF and verbal ability by evaluating two statistical models to identify mediators of SES differences in preschool readiness. In a baseline model controlling for general intelligence and processing speed, but not verbal ability, they found evidence that EF mediated SES differences in both math and reading achievement. In a second model that added a measure of vocabulary knowledge to control for differences in verbal ability, they found that EF mediated SES differences in math, but not reading, whereas vocabulary knowledge mediated SES differences in both math and reading. This demonstration that estimates of EF mediation effects are inflated in models that fail to appropriately control for verbal ability underscores the necessity of accounting for the contributions of both EF and verbal ability when modeling SES differences in achievement.

To our knowledge, only one study to date has investigated neurocognitive mediators of the SES-achievement gap in a post-elementary school sample. Lawson and Farah (2017) used structural equation modeling to evaluate whether EF mediates associations between SES and changes in reading and math achievement over a 2-year interval in a sample of 6- to 15-year-olds (M = 10.13) drawn from the NIH MRI Study of Normal Brain Development (Waber et al., 2007). EF was operationalized as a latent variable using measures of spatial memory span, spatial working memory, shifting, and verbal working memory capacity. An alternative candidate mediator, verbal memory, was operationalized as a latent variable using recall measures from the California Verbal Test of Learning for Children (Woods, Delis, Scott, Kramer, & Holdnack, 2006). Notably, the authors did not control for variation in general verbal ability (e.g., vocabulary knowledge or verbal fluency). Reading and math achievement were assessed with the Woodcock–Johnson III tests (Woodcock, McGrew, & Mather, 2001). Statistical models simultaneously tested mediation of SES-achievement associations by EF and verbal memory. EF, but not verbal memory, partially mediated the association between SES and math, but not reading achievement. Given that the study did not control for general verbal ability, which prior research has suggested is necessary for avoiding inflated estimates of EF mediation effects (Fitzpatrick et al., 2014), the specificity and magnitude of EF mediation should be interpreted with caution.

In summary, mounting evidence implicates neurocognitive functioning as an important mechanism contributing to the SES gradient in academic achievement. However, several critical gaps in the literature need to be addressed to improve our understanding and increase its value for educators. First, very few studies have simultaneously evaluated variation in SES, neurocognitive function, and achievement, a prerequisite for establishing mediation, and the existing literature is based almost entirely on preschool- and elementary-age samples. More work is needed evaluating neurocognitive mediation of SES-achievement associations in older youth to establish the generalizability of findings from younger samples. Second, most work to date has evaluated a limited set of hypothesized mediators and has not always accounted for SES-related differences in general verbal ability. To minimize confounding and improve

specificity, studies are needed that simultaneously test candidate mediators. Third, because most studies have administered neuropsychological and achievement tests concurrently, correlations may be inflated by transient confounders (e.g., a sleepy child may underperform on both tests); more studies are needed that measure neurocognitive function prior to assessment of academic achievement. Finally, research is needed to bridge the gap between the laboratory and the classroom (Bornstein & Putnick, 2019). In each of the SES-achievement mediation studies reviewed above, academic achievement was assessed in a one-on-one home or laboratory setting with subtests from the Woodcock–Johnson battery. Notwithstanding the excellent psychometric properties of such individually administered tests, they lack the concrete real-world consequences of state-mandated, group-administered assessments of academic proficiency that are often tied to student promotion, permission to enroll in challenging coursework, access to teachers certified in gifted education, and even college admissions.

This study aims to address each of these gaps in the literature by evaluating neurocognitive mediators of SES differences in middle-school academic achievement. We investigate these processes in an ethnically and socioeconomically diverse sample of youth currently enrolled in a longitudinal study of family processes and child development (the Parenting Across Cultures study), whose data have been linked to administrative records of performance on state-mandated, school-administered tests of reading and math proficiency. We use structural equation modeling to test the hypothesis that EF (measured as a latent variable) and verbal fluency each partially mediates associations between SES and reading and math achievement, such that children from higher-SES families will, on average, exhibit greater EF and verbal fluency than their peers from lower-SES families, which will in turn be associated with increased academic achievement (see Figure 1). To generate more specific testable hypotheses for future confirmatory research, we then conduct exploratory path analysis using manifest variables to estimate the degree to which each candidate neurocognitive mediator mediates SES differences in achievement (see Figure 2).

2 | METHOD

Data for this study were collected as part of a prospective longitudinal study of parenting and child adjustment being conducted with a sample of 8-year-old children and their families recruited from a mid-sized city in the Southeastern United States (see http://parentingacrosscultures.org for overview). After obtaining university Institutional Review Board approval and approval from the appropriate elementary school authorities (research review board and school principals), families were recruited from 15 public and two private elementary schools, using recruitment letters written in both English and Spanish. Interviews with 311 families were completed, including 109 European American, 99 Latin American (primarily recent arrivals to the city with more than half from Mexico and with smaller numbers from El Salvador, Guatemala, Honduras, and other Latin American countries), and 103 African American. Following this initial assessment, conducted when the child was (on average) 8 years old, families were interviewed annually; as of this writing, eight waves of interviews have been completed. For this study, analyses were limited to the 203 families for whom state-administered end-of-grade (EOG) test scores in reading and math were available for the child's 7th grade year. This subsample did not significantly differ from the subsample of participants missing EOG test scores on family income, parental education or marriage status, or child age, sex, or ethnicity (all subsample comparison *p*-values >.05). Table 1 presents demographic characteristics of the 203 families at the initial assessment. On the basis of the similarities in demographic statistics between our sample and the population of the study site (see https://www.census.gov/quickfacts/durhamcountynorthcarolina), we conclude that our sample is generally representative of the local population.

2.1 | Procedures and measures

This study uses data collected at four time points, including the initial interview assessment (age 8), annual follow-up assessments at years two (age 9) and three (age 10), and administrative records collected at the end of the child's 7th grade year (age 13). Interview assessments lasted 1.5–2 hr and were conducted in participants' homes or at another location (e.g., public library) chosen by the participants. Interviewers traveled to these sites in teams of two or three, and each family member was interviewed by a different interviewer in a place out of hearing of the other family members. We estimated socioeconomic status using questionnaire-based interview data collected from parents at the first two assessments. Neurocognitive performance was assessed with a battery of computerized performance tasks completed by children at the age-10 assessment. Academic achievement scores were derived from administrative records collected at the end of the child's 7th grade year.

2.1.1 | Socioeconomic status

Socioeconomic status was measured as a composite variable based on parents' responses to questions about educational attainment and family income. In the first three years of the project (child ages 8–10), either the mother or father completed a demographic questionnaire that included questions about the number of 'years of formal education' attained by oneself and one's spouse or partner, if applicable. We computed an index of educational attainment as the mean of all available reports. At the age-9 and –10 assessments, the demographic questionnaire included an item asking the respondent to 'indicate the gross annual income of your family' on a 10-point scale with options ranging from 'up to $5,000' to 'beyond $81,000'. We computed an index of family

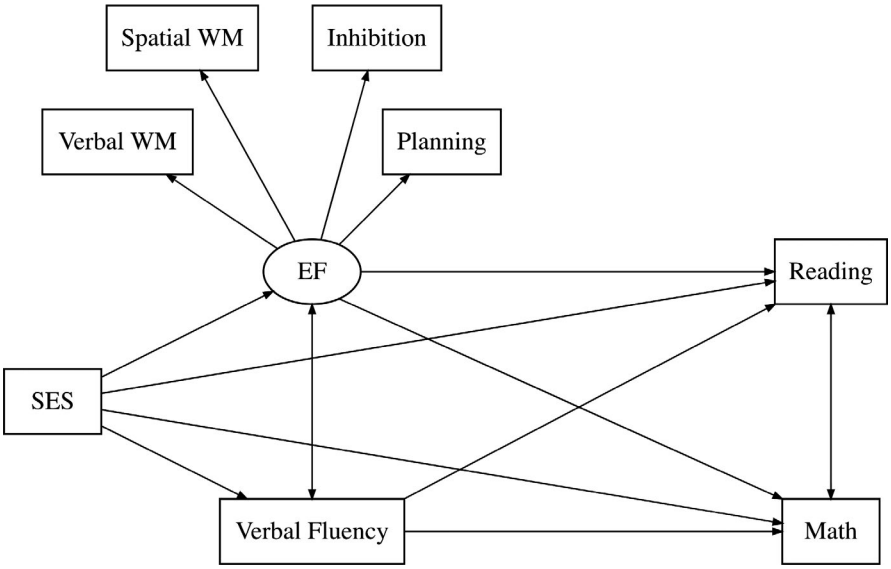

FIGURE 1 Latent variable model of direct and indirect effects of SES on academic achievement. Variance parameters are omitted but are reported in Supplemental Materials. SES, socioeconomic status; WM, working memory; EF, executive function.

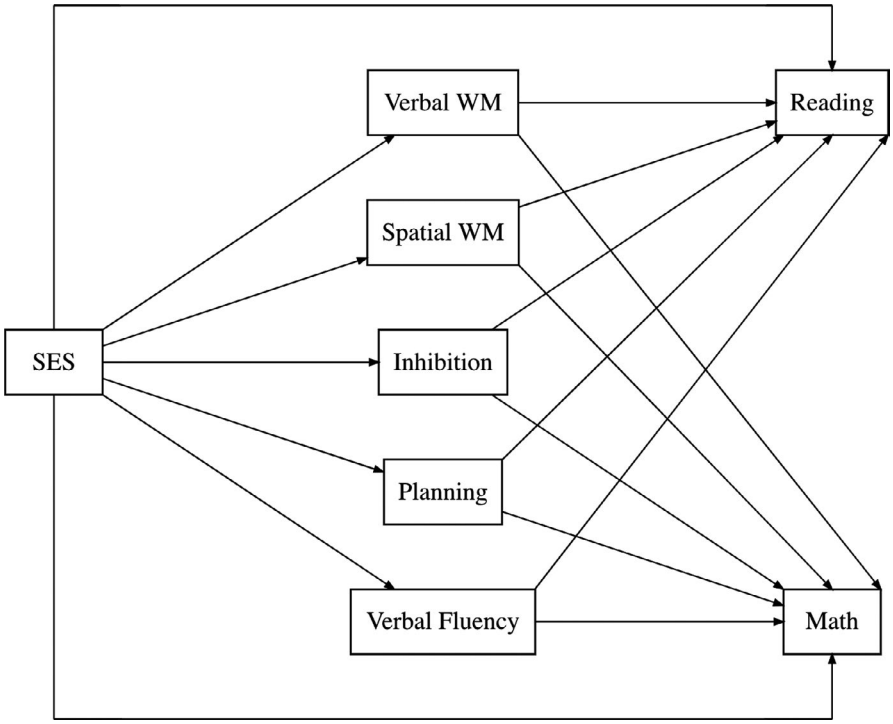

FIGURE 2 Manifest variable model of direct and indirect effects of SES on academic achievement. Variance and covariance parameters are omitted but are reported in Supplemental Materials. SES, socioeconomic status; WM, working memory

income as the mean of these two reports. Finally, we computed a composite index of socioeconomic status as the mean of standardized scores for parental educational attainment and family income (Cronbach's α = 0.83).

2.1.2 | Neurocognitive performance measures

As part of the age-10 assessment, children completed a set of widely used neurocognitive performance tasks. This study uses data from four tasks measuring components of executive function (Verbal Working Memory, Spatial Working Memory, Response Inhibition, and Strategic Planning), and one measure of Verbal Fluency.

Verbal working memory

We assessed Verbal Working Memory using an item recognition memory task (Thompson-Schill et al., 2002). On each trial of this task, participants saw four probe letters on the screen, followed by a brief delay. They were then presented a single target letter and asked whether the target was among the four probes. In half of the trials, the probe item was a member of the target data set (i.e., 'positive' trials); in the other half of the trials, the probe item was not a member of the target data

TABLE 1 Demographic characteristics of analytic sample

Variable	%	M	*SD*
Male	50.2	—	—
European American	32.5	—	—
African American	33.5	—	—
Latin American	34.0	—	—
Single Parent	23.8	—	—
Family Income ($)	—	44,500.0	28,460.8
Education	—	13.3	3.8
Child Age (Y1)	—	8.6	0.6
Child Age (Y2)	—	9.6	0.6
Child Age (Y3)	—	10.6	0.7
Child Age (Y4)	—	13.2	0.4

Note: Families were coded as single-parent if the parent reported the absence of a partner in the home at both of the years 1 and 2 assessments. Family income was estimated from parent reports at years 2 and 3 on a scale with income range response options. For each report, we estimated income as the midpoint of the response range, and computed the mean from the two reports. Education was estimated as the mean of parent reports at years 1–3 of the number of 'years of formal education' attained by oneself and one's spouse or partner, if applicable.

set (i.e., 'negative' trials). To respond accurately, participants pressed a key corresponding to *yes* for positive and *no* for negative trials.

Each participant completed four blocks of experimental trials and one block of control trials; each block included 40 trials. For experimental trials, the trial sequence was manipulated to vary the degree to which items from previous trials would interfere with accurate recognition of target items on current trials. Half of the trials used probe letters that appeared in the previous target set (not the one against which participants are currently comparing). Thus, these 'recent' trials introduce interference to the task; if participants fail to effectively update the working memory buffer by clearing items from previous trials and adding items from the current trial, they might inaccurately identify the probe as a member of the target set of letters. We calculated a Verbal Working Memory score as the proportion of accurate responses on this set of 80 high-difficulty trials.

Spatial working memory

Spatial working memory was assessed using a computerized task designed to evaluate an individual's capacity to maintain information in spatial working memory as well as to retrieve it (Chein & Morrison, 2010). Participants were presented with a series of red squares on a grid, one at a time. They were then instructed to recall the order in which the red squares appeared on the grid. Thus, the task required recall of a sequence and the location of the items. The task is 'computer adaptive'; when the participant responded correctly, the task became increasingly more difficult, offering an additional square to remember. The number of test items increased until the participant failed to correctly recall two successive trials at a given list length. A participant's Spatial Working Memory was defined as the maximum list length for which all items were recalled in the correct serial order.

Response inhibition

A computerized version of the classic Stroop color-word task was administered to assess prepotent response inhibition (Stroop, 1935). On each trial, the participant was presented a color-word (e.g., 'blue', 'yellow') and instructed to identify the color in which the word was printed (while ignoring the semantic meaning of the word) by pressing a corresponding key as quickly as possible. Trials varied on whether the color-word and the printed color of the word were congruent or incongruent. Participants completed two 48-trial experimental blocks. The first block included an equal mix of congruent and incongruent trials, and the second included a greater number of congruent than incongruent trials. Utilizing all trials, we calculated an interference effect for accuracy as the difference in ratio of accurate responses on incongruent versus congruent trials. To allow interpretation of Stroop results as a capacity, we reverse-scored the variable, such that higher scores represent stronger inhibition of attention to distracting stimuli.

Strategic planning

A computerized version of the classic Tower of London task was administered to assess strategic planning and impulse control (Berg & Byrd, 2002; Shallice, 1982). On each trial, the participant is presented with pictures of two sets of three colored balls distributed across three rods, the first of which can hold three balls, the second only two balls, and the last only one ball. The first picture shows the starting position of the three balls, and the second depicts the goal position. The participant is asked to move the balls in the starting arrangement to match the other arrangement in as few moves as necessary, using the computer cursor to 'drag' and 'drop' each ball. Five sets of four problems are presented, beginning with those that can be solved in three moves and progressing to those that require a minimum of seven moves. The trial is considered successfully solved if the solution is correctly submitted within a time limit of 160 s. We computed an index of Strategic Planning as the percentage of trials with perfect solutions (i.e., trials solved in the minimum number of moves), a measure of optimal planning and execution of the task (Albert & Steinberg, 2011).

Verbal fluency

A measure of verbal fluency asked participants to speak, in 1 min, as many words as possible which either began with a specific letter (three trials) or were members of a category (e.g., fruits) (three trials). For each trial, the interviewer recorded the number of unique spoken words. A Verbal Fluency score was computed by averaging the number of words generated for each of the six lists.

2.1.3 | Academic performance

To measure academic performance, we used administrative records of state-mandated EOG test scores in reading and math from the child's 7th grade year. All 3rd- through 8th-grade students in North Carolina are required to take EOG achievement tests in both reading and math.

TABLE 2 Means, standard deviations, and correlations with confidence intervals

Variable	M	*SD*	1	2	3	4	5	6	7	8
1. Income	44,500.00	28,460.76								
2. Education	13.33	3.85	0.73** [.66, 0.79]							
3. Reading	50.10	32.45	0.61** [.52, 0.69]	0.60** [.50, 0.68]						
4. Math	48.86	31.92	0.57** [.47, 0.66]	0.49** [.37, 0.59]	0.79** [.74, 0.84]					
5. Verbal Fluency	9.78	2.59	0.46** [.34, 0.57]	0.47** [.34, 0.58]	0.50** [.38, 0.61]	0.43** [.30, 0.54]				
6. Verbal WM	6.05	1.28	0.30** [.16, 0.43]	0.21** [.06, 0.34]	0.40** [.27, 0.52]	0.46** [.33, 0.57]	0.41** [.28, 0.53]			
7. Spatial WM	4.51	1.40	0.06 [−0.09, 0.21]	0.06 [−0.10, 0.20]	0.18* [.03, 0.32]	0.28** [.14, 0.41]	0.21** [.06, 0.35]	0.29** [.14, 0.42]		
8. Planning	0.34	0.11	0.24** [.09, 0.38]	0.13 [−0.02, 0.28]	0.22** [.08, 0.36]	0.33** [.19, 0.46]	0.17* [.02, 0.31]	0.27** [.13, 0.40]	0.26** [.11, 0.39]	
9. Inhibition	−0.09	0.13	0.24** [.09, 0.38]	0.13 [−0.02, 0.27]	0.16* [.01, 0.30]	0.15* [.00, 0.30]	0.16* [.01, 0.31]	0.19* [.04, 0.33]	0.04 [−0.11, 0.19]	0.14 [−0.01, 0.29]

Note: WM = Working Memory. Prior to data analysis, SES was computed as the average of standardized (Mean = 0; *SD* = 1) scores for education and income.

*$p < .05$.

**$p < .01$.

We opted to use grade-7 scores because all children in our sample had completed the age-10 battery of neurocognitive performance measures before the grade-7 EOG testing period, providing the sequential ordering required to evaluate neurocognitive performance as a predictor of EOG scores. EOG tests in reading comprehension measure the ability to demonstrate understanding of a written passage and knowledge of vocabulary. EOG tests in math measure proficiency in five areas: numbers and operations; measurement; geometry; data analysis and probability; and algebra. EOG test score files included raw test scores, student grade level, and year of testing. Because state-level mean scores for the tests varied substantially based on the year of testing, we standardized participants' scores based on the state mean and standard deviation for the corresponding year. Using this method, we transformed each student's raw score to a percentile score, which indicates the percentage of students in the state scoring below that student for the given year.

2.2 | Data analysis

All structural equation models were tested using the R package 'lavaan' (Rosseel, 2012). We used a full information maximum likelihood estimator with robust standard errors to account for data missing at random and non-normality. We define acceptable model fit as a χ^2 -to-*df* ratio less than 3, comparative fit index (CFI) greater than or equal to 0.95, root mean squared error of approximation (RMSEA) less than 0.08, and standardized root mean square residual (SRMR) less than or equal to 0.10 (Schermelleh-Engel, Moosbrugger, & Müller, 2003). After establishing acceptable fit for each model, we evaluate the statistical significance of indirect effects using bias-corrected bootstrap confidence intervals (95% CIs) based on 5,000 draws with replacement; effects are deemed significant if the CI does not include zero (Preacher & Hayes, 2008). We estimate the magnitude of each significant indirect effect as a mediation ratio (indirect/total effects; Ditlevsen, Christensen, Lynch, Damsgaard, & Keiding, 2005).

TABLE 3 Factor loadings for latent variable model of executive function

	Std. Beta	Raw Beta	*SE*
Verbal WM	0.68	1.00	0.00
Spatial WM	0.43	0.69	0.16
Planning	0.43	0.05	0.01
Response inhibition	0.24	0.04	0.01

Note: WM = Working Memory. Standardized factor loadings are reported as Std. Beta. For scale identification, the raw loading for Verbal WM was set to 1.

3 | RESULTS

Means, *SDs*, and intercorrelations of all continuous variables are reported in Table 2. All reported beta coefficients are derived from a fully standardized model.

3.1 | Do executive function and verbal fluency mediate SES differences in reading and math achievement?

We first evaluated the fit of Model 1 (Figure 1), in which executive function is estimated as a latent variable, and SES, verbal fluency, and reading and math achievement are manifest variables. The model fit the data well: χ^2 (14, N = 203) = 14.03, p = .448, *CFI* = 1.00, *RMSEA* = 0.01, *SRMR* = 0.03, *AIC* = 5,069.44, *BIC* = 5,162.21. Factor loadings for the latent EF variable are reported in Table 3. Latent EF accounted for 46.19% of the observed variation in verbal working memory, 18.36% of spatial working memory, 18.60% of planning, and 5.76% of response inhibition.[1]

Altogether, the model explained 52.39% of the variation in reading scores and 57.27% of math scores. Model results are depicted in Figure 3 and reported in detail in Table 4; full model results, including variance and covariance estimates, are provided in Table S1. SES

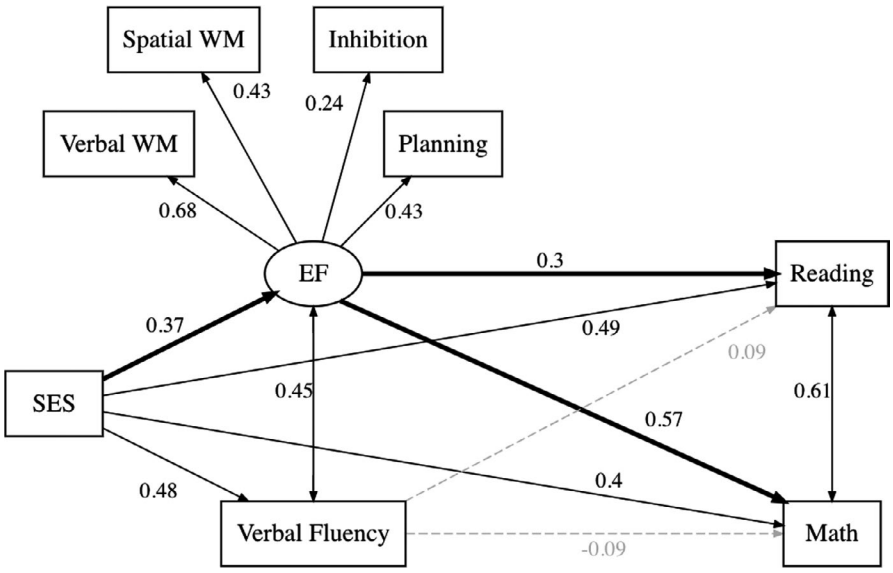

FIGURE 3 Latent variable model of direct and indirect effects of SES on academic achievement. Standardized beta coefficients are reported for each path. Statistically significant (p < .05) paths are depicted as solid black lines; non-significant paths are depicted as gray dashed lines. Bold lines represent statistically significant indirect effects from SES to Reading and/or Math achievement. Variance parameters are omitted but are reported in Supplemental Materials. SES, socioeconomic status; WM, working memory; EF, executive function

TABLE 4 Model 1 coefficient estimates

Path	Std. Beta	CI (low)	CI (high)	Beta	*SE*	z	*p*
SES->Reading	0.49	0.34	0.60	17.17	2.21	7.76	<.001
SES->Math	0.40	0.25	0.54	13.66	2.53	5.39	<.001
SES->Verbal	0.48	0.40	0.58	1.33	0.17	7.96	<.001
SES->EF	0.37	0.20	0.54	0.34	0.09	3.93	<.001
Verbal->Reading	0.09	−0.06	0.25	1.17	0.89	1.31	.190
EF->Reading	0.30	0.10	0.49	11.23	4.06	2.77	.006
Verbal->Math	−0.09	−0.29	0.08	−1.12	1.15	−0.97	.331
EF->Math	0.57	0.37	0.82	21.08	5.89	3.58	<.001

Note.: SES = Socioeconomic Status. Verbal = Verbal Fluency. EF = Executive Function. CI (low) and CI (high) represent the lower and upper bounds of the 95% confidence interval for the standardized point estimate, respectively. SE, standard error.

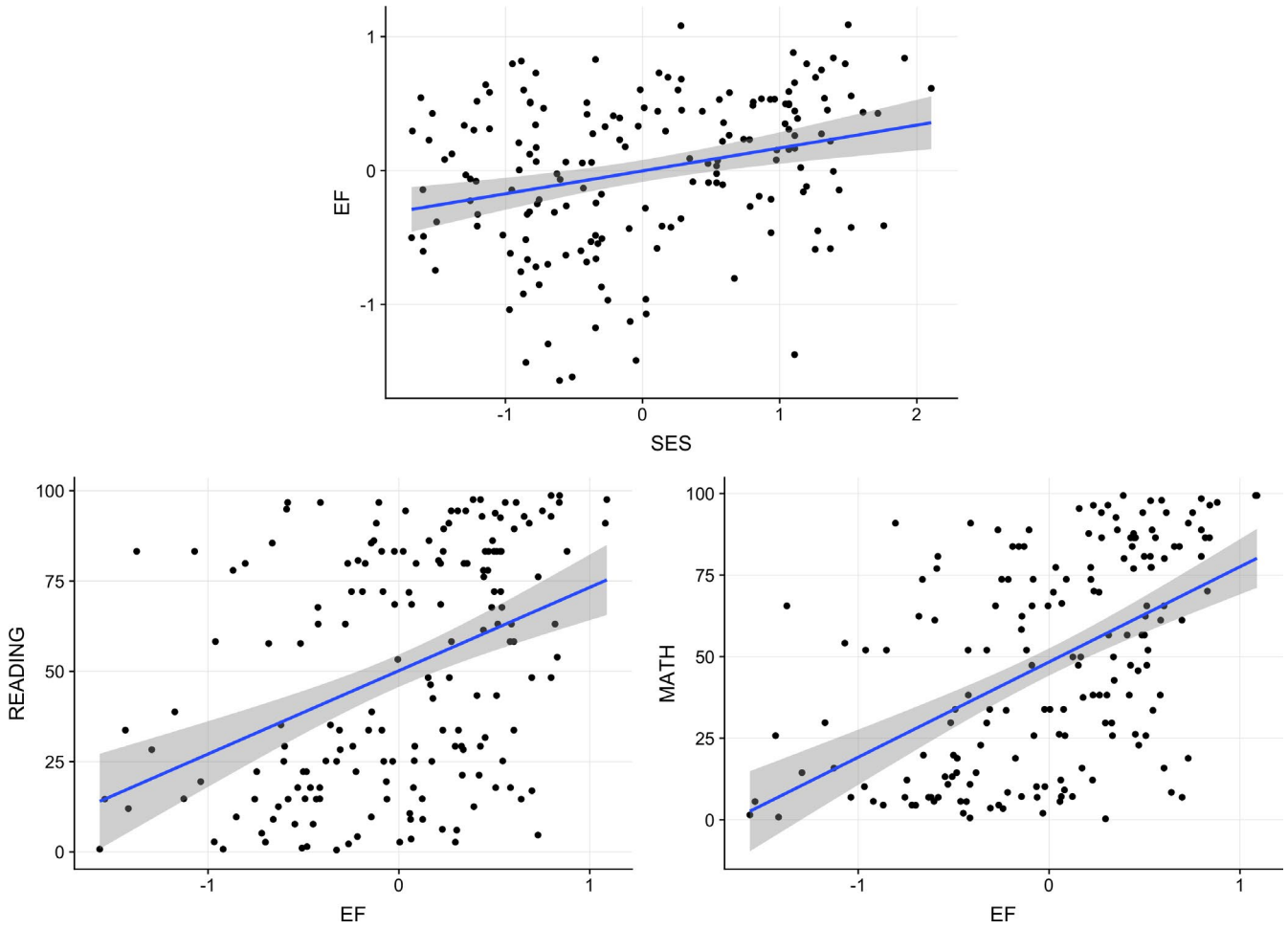

FIGURE 4 Associations between SES, Executive Function, and Reading and Math scores. Executive function (EF) scores are extracted factor scores from the measurement model illustrated in Figure 1. SES, socioeconomic status

had significant direct effects on verbal fluency (β = 0.48, 95% CI [0.40, 0.58]), EF (β = 0.37, 95% CI [0.20, 0.54]), reading (β = 0.49, 95% CI [0.34, 0.60]), and math (β = 0.40, 95% CI [0.25, 0.54]), all *ps* < .001. Latent EF had significant effects on both reading (β = 0.30, 95% CI [0.10, 0.49]) and math (β = 0.57, 95% CI [0.37, 0.82]) scores, such that a 1 *SD* increase in EF is associated with scoring 0.30 *SDs* higher on the reading test and 0.57 *SDs* higher on the math test. In contrast, verbal fluency paths to reading (β = 0.09, 95% CI [−0.06, 0.25]) and math (β = −0.09, 95% CI [−0.29, 0.08]) scores were not significant. Associations between SES, EF, and reading and math scores are illustrated in Figure 4.

Model results provide evidence that in addition to the direct effects of SES on math and reading scores, SES had indirect effects on achievement through its effect on executive function (Table 5). In total (i.e., including direct and indirect effects), a 1 *SD* increase in SES

TABLE 5 Model 1: Direct and indirect effects of SES on reading and math scores

Effect	Std. Beta	CI (low)	CI (high)	Mediation ratio
Direct (SES->Reading)	0.49	0.34	0.60	0.76
SES->EF->Reading	0.11	0.04	0.23	0.17
SES->Verbal->Reading	0.04	−0.03	0.13	0.07
Total (SES->Reading)	0.65	0.56	0.71	—
	—	—	—	—
Direct (SES->Math)	0.40	0.25	0.54	0.70
SES->EF->Math	0.21	0.10	0.34	0.37
SES->Verbal->Math	−0.04	−0.14	0.04	−0.08
Total (SES->Math)	0.57	0.49	0.63	—

Note: SES = Socioeconomic Status. Verbal = Verbal Fluency. EF = Executive Function. CI (low) and CI (high) represent the lower and upper bounds of the bias-corrected bootstrap confidence intervals (95% CIs), based on 5,000 draws with replacement; effects are deemed significant if the CI does not include zero. Mediation Ratio was calculated by dividing the effect estimate (Beta) by the total SES-to-achievement effect.

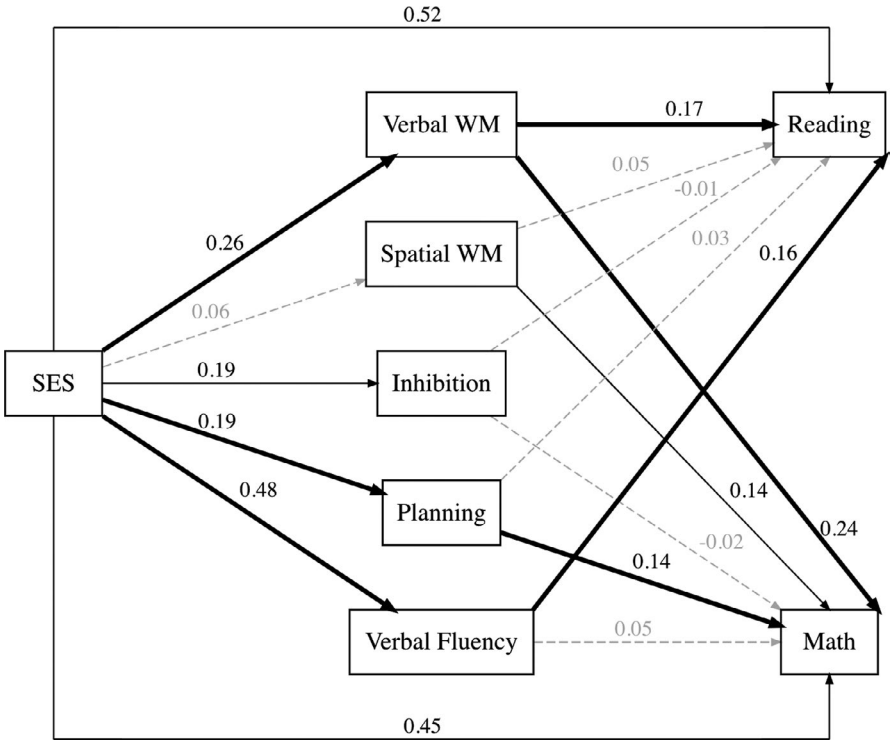

FIGURE 5 Manifest variable model of direct and indirect effects of SES on academic achievement. Standardized beta coefficients are reported for each path. Statistically significant ($p < .05$) paths are depicted as solid black lines; non-significant paths are depicted as gray dashed lines. Bold lines represent statistically significant indirect effects from SES to Reading and/or Math achievement. Variance and covariance parameters are omitted but are reported in Supplemental Materials. SES, socioeconomic status; WM, working memory

is associated with a 0.65 *SD* increase in reading score and a 0.57 *SD* increase in math score. Significant indirect effects of SES through EF accounted for 17.12% of the total SES effect on reading scores ($\beta_{\text{SES->EF->Reading}}$ = 0.11, 95% CI [0.04, 0.23]) and 37.36% of the total SES effect on math scores ($\beta_{\text{SES->EF->Math}}$ = 0.21, 95% CI [0.10, 0.34]). Verbal fluency did not mediate SES effects on either reading or math scores.

3.2 | Which specific neurocognitive skills mediate SES differences in achievement?

To evaluate the degree to which each candidate neurocognitive skill mediates SES differences in achievement, we estimated Model 2, which treats each of the EF indicators from Model 1 as a distinct manifest variable that potentially mediates SES-related differences in achievement (see Figure 2). Because Model 2 estimates all covariances between manifest variables, it is considered saturated, precluding measures of model fit. Altogether, the model explained 49.44% of the variation in reading scores and 46.25% of math scores. Model results are depicted in Figure 5 and reported in detail in Table 6; full model results are reported in Table S2.

Given the lack of an evidence base to motivate specific hypotheses regarding the relative importance of each EF subcomponent to the SES-achievement gap, we consider this an exploratory analysis; as such, although we report the results of significance tests, we encourage the reader to attribute greater informational value

TABLE 6 Model 2 coefficient estimates

Path	Std. Beta	CI (low)	CI (high)	beta	*SE*	z	*p*
SES->Reading	0.52	0.40	0.63	18.16	2.13	8.53	<.001
SES->Math	0.45	0.33	0.57	15.40	2.13	7.24	<.001
SES->Verbal WM	0.26	0.13	0.39	0.36	0.09	3.86	<.001
SES->Verbal Fluency	0.48	0.38	0.58	1.33	0.17	7.96	<.001
SES->Inhibition	0.19	0.08	0.31	0.03	0.01	2.95	.003
SES->Spatial WM	0.06	−0.07	0.19	0.09	0.10	0.87	.386
SES->Planning	0.19	0.05	0.33	0.02	0.01	2.69	.007
Verbal WM->Reading	0.17	0.05	0.30	4.33	1.64	2.64	.008
Verbal Fluency->Reading	0.16	0.04	0.28	2.02	0.71	2.85	.004
Inhibition->Reading	−0.01	−0.13	0.10	−3.59	14.00	−0.26	.798
Spatial WM->Reading	0.05	−0.09	0.18	1.12	1.54	0.73	.466
Planning->Reading	0.03	−0.09	0.15	9.32	17.00	0.55	.583
Verbal WM->Math	0.24	0.12	0.37	6.02	1.63	3.69	<.001
Verbal Fluency->Math	0.05	−0.09	0.19	0.65	0.86	0.76	.449
Inhibition->Math	−0.02	−0.13	0.09	−4.89	12.93	−0.38	.705
Spatial WM->Math	0.14	−0.01	0.27	3.11	1.59	1.96	.050
Planning->Math	0.14	0.02	0.25	39.56	17.86	2.21	.027

Note: SES = Socioeconomic Status. WM = Working Memory. CI (low) and CI (high) represent the lower and upper bounds of the 95% confidence interval for the standardized point estimate, respectively. SE, standard error.

to measures of relative effect size (Cumming, 2014), including (a) SES–>Mediator coefficients (the number of *SDs*) each neurocognitive ability is expected to change given a 1 *SD* increase in SES); (b) Mediator–>Test Score coefficients (the number of *SDs* that a student's test score is expected to change given a 1 *SD* increase in a given neurocognitive ability); and (c) indirect effect estimates (the number of *SDs* that a student's test score is expected to change given a 1 *SD* increase in SES, through its effect on a given neurocognitive ability). These effect sizes are illustrated in Figure 6.

Consistent with Model 1 results, parameter estimates from Model 2 indicated that children from higher-SES homes scored higher on tests of verbal fluency (β = 0.48, 95% CI [0.38, 0.58]), reading (β = 0.52, 95% CI [0.40, 0.63]), and math (β = 0.45, 95% CI [0.33, 0.57]), all *ps* <.001. In addition, direct paths were significant from SES to verbal working memory (β = 0.26, 95% CI [0.13, 0.39], *p* =< .001), response inhibition (β = 0.19, 95% CI [0.08, 0.31], *p* = .003), and planning (β = 0.19, 95% CI [0.05, 0.33], *p* = .007), but not from SES to spatial working memory (β = 0.06, 95% CI [−0.07, 0.19], *p* = .386).

Also consistent with Model 1, individual differences in executive function skills explained substantial variability in academic achievement scores. Specifically, paths to math achievement were significant from verbal working memory (β = 0.24, 95% CI [0.12, 0.37], *p* =<.001), spatial working memory (β = 0.14, 95% CI [−0.01, 0.27], *p* = .050), and planning (β = 0.14, 95% CI [0.02, 0.25], *p* = .027), but not response inhibition (β = −0.02, 95% CI [−0.13, 0.09], *p* = .705) or verbal fluency (β = 0.05, 95% CI [−0.09, 0.19], *p* = .449). For reading achievement, the only significant EF path was from verbal working memory (β = 0.17, 95% CI [0.05, 0.30], *p* = .008); paths from spatial working memory (β = 0.05, 95% CI [−0.09, 0.18], *p* = .466), planning (β = 0.03, 95% CI [−0.09, 0.15], *p* = .583), and response inhibition (β = −0.01, 95% CI [−0.13, 0.10], *p* = .798) were not significant. In contrast to Model 1 results, reading achievement was also significantly predicted by verbal fluency (β = 0.16, 95% CI [0.04, 0.28], *p* = .004).

Results of the indirect effects analysis provide further evidence highlighting the role of verbal working memory as a mediator of SES differences in both math and reading achievement (see Table 7 and Figure 6). Significant indirect effects of SES through verbal working memory account for 11.01% of the total SES effect on math scores ($\beta_{\text{SES->VWM->Math}}$ = 0.06, 95% CI = 0.02, 0.12) and 6.81% of the total SES effect on reading scores ($\beta_{\text{SES->VWM->Reading}}$ = 0.04, 95% CI = 0.01, 0.10). For math scores, a small but statistically significant indirect effect of SES through strategic planning accounts for 4.60% of the total SES effect ($\beta_{\text{SES->TOL->Math}}$ = 0.03, 95% CI = 0, 0.07). For reading scores, a relatively large indirect effect of SES through verbal fluency accounts for 11.91% of the total SES effect ($\beta_{\text{SES->Verbal->Reading}}$ = 0.08, 95% CI = 0.02, 0.14). No other indirect effects were statistically significant.

Because estimates of indirect effects may be attenuated in models simultaneously evaluating multiple collinear mediators (Preacher & Hayes, 2008), we conducted a series of model comparison analyses to assess the relative importance of specific EF variables for explaining SES-achievement associations. First, to evaluate the ability of each EF variable to function as a proxy for latent EF, we estimated parallel mediation models (i.e., each of the four candidate EF mediators were evaluated separately, still covarying for verbal fluency). Consistent with the results of the multiple mediator model, verbal working memory mediated a larger proportion of SES effects on

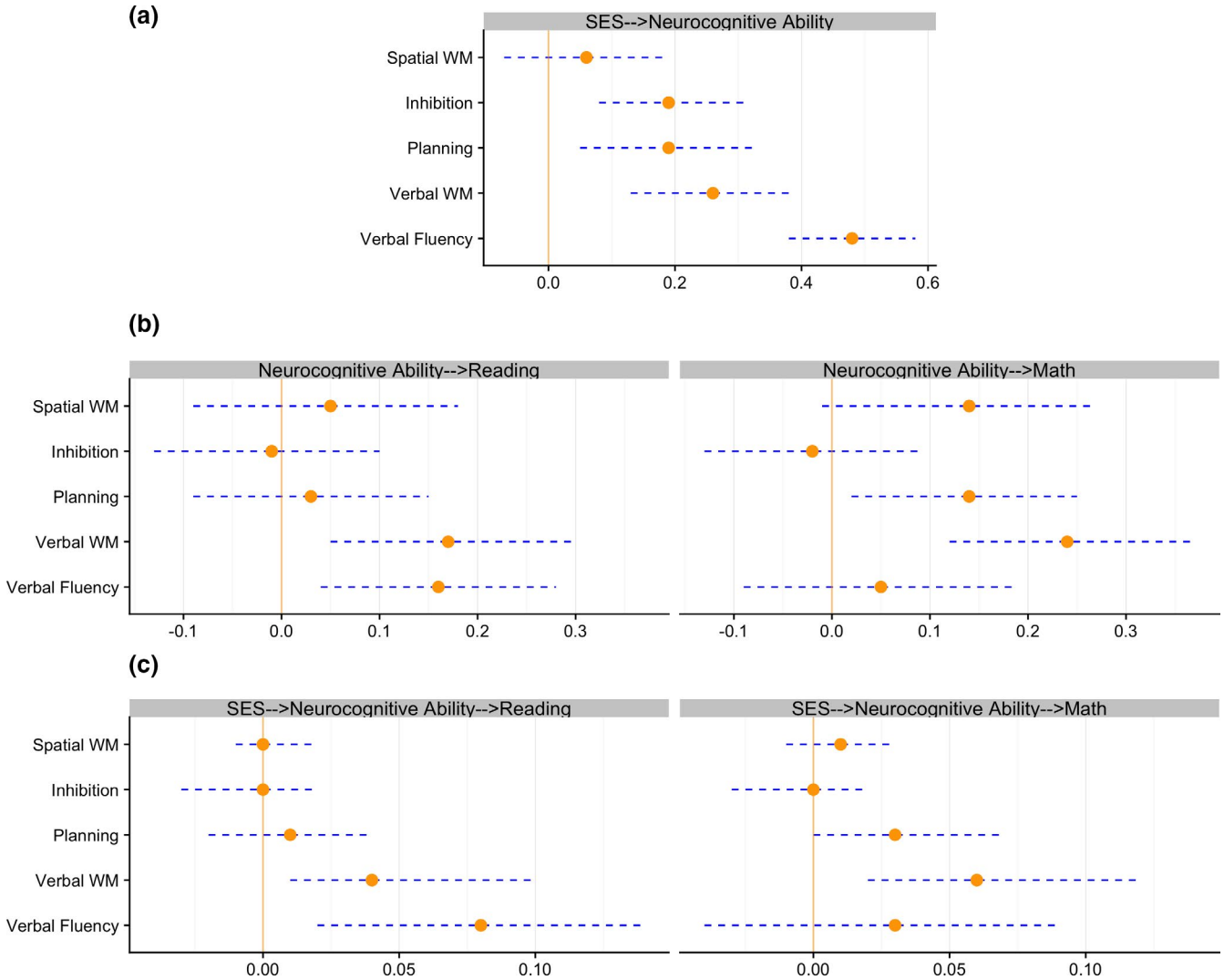

FIGURE 6 Comparison of effect sizes for neurocognitive pathways linking SES to reading and math achievement. Effect estimates (i.e., standardized beta coefficients) are represented by dots; 95% confidence intervals are represented by dashed lines. Panel A depicts the size of effects linking SES to each neurocognitive ability, controlling for all other neurocognitive abilities; coefficients indicate the number of *SDs* each neurocognitive ability is expected to change given a 1 *SD* change in SES. Panel B depicts the size of effects linking each neurocognitive ability to an academic achievement score, controlling for SES and all other neurocognitive abilities. Coefficients indicate the number of *SDs* that a reading or math score is expected to change given a 1 *SD* change in a given neurocognitive ability. Panel C depicts the size of indirect effects from SES to achievement through each neurocognitive ability; coefficients indicate the number of *SDs* that a reading or math score is expected to change given a 1 *SD* change in SES, attributable to a given neurocognitive ability

both reading (8%) and math (12%) than any of the three other EF variables (see Table S3 for full results). Indeed, verbal working memory accounted for nearly as much of the SES-achievement effect as the combined effects of all four EF variables in the multiple mediator model, which mediated 8% of SES effects on reading and 16% of SES effects on math. However, even this best single-EF-mediator model accounted for much less of the SES-achievement association than our latent variable measure of EF, which mediated 17% of the SES gap in reading achievement and 37% of the SES gap in math achievement.

Next, to evaluate the incremental mediation effects of each EF variable, we estimated four variations of the multiple mediator model. For each EF variable, we computed a model that constrained the *a* (SES->Mediator) and *b* (Mediator->Achievement) paths to zero while estimating all other paths specified in Model 2. Because each of these models is nested within Model 2, we are able to evaluate loss of model fit resulting from parameter constraints using χ^2 comparison. Results again support the importance of verbal working memory as a mediator of SES-achievement associations. Compared to the full unconstrained model, the model constraining SES->VerbalWM->Achievement paths to zero showed a significant loss of model fit (χ^2 *diff* (3) = 26.53, $p < .001$) and a reduction in total EF mediation effects for both reading (from 7.7% to 1.1%) and math (from 16.3% to 3.7%). Results also support a small but significant incremental effect for strategic planning. The model constraining SES->Planning->Achievement paths to zero showed a

TABLE 7 Model 2: Direct and indirect effects of ses on reading and math scores

Effect	Std. Beta	CI (low)	CI (high)	Mediation ratio
Direct (SES->Reading)	0.52	0.40	0.63	0.80
SES->Verbal->Reading	0.08	0.02	0.14	0.12
SES->VWM->Reading	0.04	0.01	0.10	0.07
SES->SWM->Reading	0.00	−0.01	0.02	0.00
SES->Planning->Reading	0.01	−0.02	0.04	0.01
SES->Inhibition->Reading	0.00	−0.03	0.02	0.00
Total (SES->Reading)	0.65	0.57	0.72	—
	—	—	—	—
Direct (SES->Math)	0.45	0.33	0.57	0.79
SES->Verbal->Math	0.03	−0.04	0.09	0.04
SES->VWM->Math	0.06	0.02	0.12	0.11
SES->SWM->Math	0.01	−0.01	0.03	0.01
SES->Planning->Math	0.03	0.00	0.07	0.05
SES->Inhibition->Math	0.00	−0.03	0.02	−0.01
Total (SES->Math)	0.57	0.48	0.65	—

Note: SES = Socioeconomic Status. Verbal = Verbal Fluency. VWM = Verbal Working Memory. SWM = Spatial Working Memory. CI (low) and CI (high) represent the lower and upper bounds of the bias-corrected bootstrap confidence intervals (95% CIs), based on 5,000 draws with replacement; effects are deemed significant if the CI does not include zero. Mediation Ratio was calculated by dividing the effect estimate (Beta) by the total SES-to-achievement effect.

significant loss of model fit (χ^2 *diff* (3) = 13.39, p = .004) and a reduction in EF mediation for reading (from 7.7% to 5.7%) and math (from 16.3% to 10.6%). Models constraining mediation pathways for response inhibition and spatial working memory, respectively, did not result in significant loss of model fit, suggesting that their roles as mediators of SES-achievement effects are redundant to other variables in the model. Full model comparison results are reported in Table S4.

Finally, to evaluate the degree to which each EF variable contributed to the mediation effects identified for the latent EF variable, we estimated four variations of Model 1. Each model variation omitted one of the four indicators from the EF measurement model while estimating all other parameters identically to Model 1. Thus, each model estimated SES->EF->Achievement effects for a slightly different version of EF. For example, in the model omitting verbal working memory, EF represents the shared variance between spatial working memory, inhibition, and planning. If the omission of verbal working memory from the latent variable model reduces the proportion of SES-achievement effects mediated by EF, this suggests that verbal working memory is a strong indicator of the aspect of EF that mediates these effects. Results support exactly this interpretation. Omission of verbal working memory as an indicator of latent EF reduced the proportion of SES-achievement effects mediated by latent EF for both reading (from 17.1% to 7.5%) and math (from 37.4% to 25.2%), further supporting the central role of verbal working memory to the EF mediation effects reported in this paper. Omission of other EF indicators did not meaningfully change results. Full model comparison results are reported in Table S5.

4 | DISCUSSION

Socioeconomic status is one of the most consistently identified and powerful predictors of academic achievement in childhood and adolescence (Bradley & Corwyn, 2002), yet the neurocognitive mechanisms underlying SES disparities in achievement remain poorly understood. Motivated by past research, we evaluated executive function and verbal fluency as candidate mediators of the SES-achievement association using longitudinal data from a diverse cohort of children and structural equation modeling. Unique to the work, we examined administrative records of performance on group-administered, state-mandated achievement tests. These ecologically valid measures may be of greater 'real-world' importance, as such testing determines student promotion standards. Consistent with prior work, children from relatively higher-SES homes performed better than their lower-SES peers on assessments of 7th grade reading and math achievement. Furthermore, we found in our primary latent variable analysis that SES disparities in both reading and math achievement are partially mediated by variation in executive function, but not verbal fluency. On average, children from higher-SES families demonstrate stronger EF capacities than their lower-SES peers, and this disparity in EF explains approximately 17% of the SES gap in reading achievement and 37% of the SES gap in math achievement.

We also addressed the question of which specific executive function abilities are most implicated in the SES-achievement gap. Results of exploratory analyses evaluating the unique role of each neurocognitive ability highlight the importance of SES-related differences in verbal working memory for explaining gaps in both reading and math

achievement. The relatively large mediation effect identified for verbal working memory compared to other executive function abilities is clearly apparent in Figure 7, which displays the size of indirect effects for each candidate mediator separately for the two modeling approaches we used. However, Figure 7 also highlights the substantially larger mediation effect of our executive function latent variable, which accounts for more than twice as much of the SES-related variance in math and reading scores than the combined effects of the manifest EF variables. As we discuss in greater depth below, this large difference in effect size highlights the challenges of interpreting the results of manifest variable, multiple-mediator models in the presence of multicollinearity (Preacher & Hayes, 2008). We conducted several sensitivity analyses to confirm the centrality of verbal working memory to EF mediation effects in this study, but still caution the reader to consider the findings as tentative. Further research is warranted to determine whether working memory is simply a more reliable measure of EF or if it is indeed the most critical domain of executive function for explaining SES-related differences in achievement.

As a whole, our results are broadly consistent with previous work identifying executive function as a critical mediator of the SES-achievement gap, while addressing several weak points in the literature. First, although previous studies demonstrated that EF mediates SES differences in performance on laboratory assessments of achievement (Crook & Evans, 2014; Dilworth-Bart, 2012; Fitzpatrick et al., 2014; G. Lawson & Farah, 2017; Nesbitt et al., 2013; NICHD Early Child Care Research Network, 2003), none had examined the role of EF in performance on the high-stakes proficiency tests that are the focus of so much instructional attention in North American schools. Given differences in test content, length, and administration setting, it remained unclear whether prior findings implicating EF in the SES-achievement gap would generalize to performance on group-administered, state-mandated achievement tests. Findings from this study provide strong support for this across-test generalization.

Second, only three prior studies evaluated EF mediation of SES-achievement with a longitudinal design (Crook & Evans, 2014; Lawson & Farah, 2017; Nesbitt et al., 2013). Others assessed EF and achievement in the same laboratory session (Dilworth-Bart, 2012; Fitzpatrick et al., 2014; NICHD Early Child Care Research Network, 2003), leaving open the possibility that correlations between EF and achievement were inflated by confounds related to the day of testing. This study demonstrates that EF (measured at age 10) mediates SES differences in achievement measured years (M = 2.5) later, strengthening the claim that individual differences in EF are a stable and enduring mechanism underlying the SES-achievement gap.

Third, results of prior studies have been mixed with respect to whether EF mediates SES differences in both math and reading achievement (Nesbitt et al., 2013; NICHD Early Child Care Research Network, 2003) or only math (Crook & Evans, 2014; Dilworth-Bart, 2012; Fitzpatrick et al., 2014; Lawson & Farah, 2017). This study, conducted with a reasonably large sample size and strong measurement of EF and achievement, provides compelling evidence that EF mediates SES differences in both math and reading achievement.

Fourth, given results of prior work implicating verbal ability as a mediator of SES differences in achievement (e.g., Beron & Farkas, 2004), evidence for EF mediation from studies that did not adequately control for verbal ability (Crook & Evans, 2014; Lawson & Farah, 2017; NICHD Early Child Care Research Network, 2003) must be interpreted with caution. In models simultaneously testing mediation by latent EF and verbal fluency, we find that EF—but not verbal fluency—partially mediates SES-achievement gaps for both math and reading. We suspect that differences in measurement and data analysis strategy may contribute to divergent findings regarding the respective roles of EF and verbal ability as mediators. In contrast to the findings from our latent variable model, exploratory analyses evaluating verbal fluency against four different manifest EF variables indicated that verbal fluency partially mediated SES differences in reading scores. The inconsistency of these findings highlights the sensitivity of standard manifest variable regression analysis to the inclusion of multiple collinear variables. Given this well-known limitation of standard regression analysis, and our demonstration that a latent varible model accounts for more than twice as much of the association between SES and achievement, we believe that latent variable modeling should be the default approach to future research in this domain.

The final weakness in the literature that our study addresses is the lack of research on neurocognitive mediation of SES differences in achievement among adolescent samples, which to our knowledge has been evaluated in only one study to date (Lawson & Farah, 2017). Similar to this study, Lawson and Farah (2017) assessed EF as a latent variable in a sample followed longitudinally from late childhood through early adolescence and found EF partially mediated SES differences in achievement. As we argued in the introduction, our study was designed to confirm and extend their findings by examining the same processes with a more ecologically valid measure of academic achievement and a more rigorous control for verbal ability. (Lawson and Farah measured academic achievement with a standard laboratory assessment and control for verbal ability with a measure of verbal memory.) We expected that our inclusion of a more rigorous control for verbal ability would result in attenuated mediation effects for EF, and were surprised to find larger mediation effects for EF and smaller effects for verbal ability than those reported by Lawson and Farah. Although the overall findings of the two studies are broadly consistent, Lawson and Farah (2017) found that EF mediated SES differences in math—but not reading—achievement, whereas we found that EF mediated both. This unexpected (but relatively minor) divergence in findings could be explained by any of several small differences in study design and sample, including that their outcome variable was operationalized as *change* in academic achievement over time, whereas this study did not covary for past academic achievement. Future research should evaluate mediation of SES differences in both baseline academic achievement and change over time to reconcile these findings.

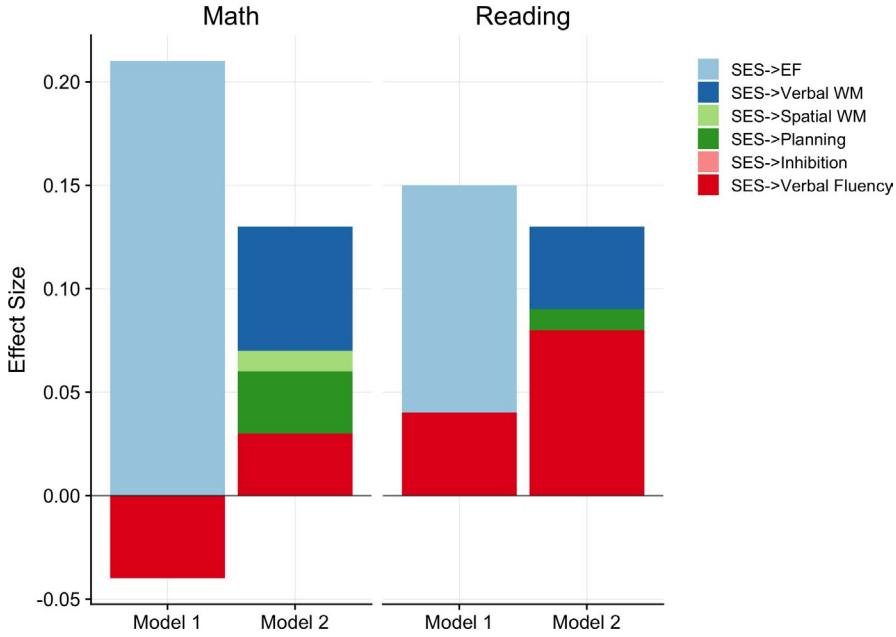

FIGURE 7 Relative magnitude of neurocognitive mediation effects estimated from latent (Model 1) and manifest (Model 2) variable models of SES-related variation in academic achievement. Each bar represents the total number of *SDs* that a reading or math score is expected to change given a 1 *SD* change in SES, due to the effects of SES on neurocognitive ability variables in the model. The portion of the indirect effect attributable to a given neurocognitive ability variable is indicated by bar color. SES, socioeconomic status; WM, working memory

In sum, several methodological strengths of this study bolster our confidence in the robustness of our central finding that executive function is an important mediator of socioeconomic variation in academic achievement. For instance, the use of multiple neurocognitive tasks to measure EF as a latent construct allowed us to minimize measurement error and increase the precision of model estimates. In addition, the longitudinal research design, wherein neurocognitive performance and academic achievement were assessed at different times and in different settings, ensured the correct temporal sequence for mediation analysis and reduced the threat of state-level confounds (e.g., sleepiness) inherent when neurocognitive performance and academic achievement are assessed at the same time. Finally, the socioeconomic and ethnic diversity of the study sample, which included roughly equal numbers of European, African, and Latin American families, suggests that study findings are likely relevant to a broad range of student populations and communities.

Despite these strengths, our capacity to identify causal pathways by which socioeconomic factors impact academic achievement is limited due to constraints of study design. Most importantly, we are not able to account for confounds arising from gene-environment correlation; it is possible (indeed, likely) that a substantial portion of SES-related variation in neurocognition and academic performance arises from parental transmission of genetic variants associated with the parents' SES and the child's achievement (Krapohl et al., 2017). However, this uncertainty regarding genetic versus. environmental causation does not necessarily undermine the relevance of this study findings for educational practice. Whether or not the learning challenges faced by socioeconomically disadvantaged students arise from genetic or environmental causes, which are inextricably intertwined, it remains important for parents, educators, and interventionists to understand these specific challenges when considering options for most effectively supporting student learning.

An additional limitation of the study is its incomplete consideration of alternative neurocognitive mediators of SES-related variation in achievement. In contrast to our multi-measure assessment of executive function as a latent variable, we assessed verbal ability with only a single verbal fluency task. Given evidence for the mediating role of verbal ability reported in some (but not all) previous studies of the SES-achievement gap (e.g., Fitzpatrick et al., 2014), it is possible that verbal ability would have emerged as a significant mediator in this study if it were measured with less error. Likewise, there is a need for research that evaluates a more comprehensive range of cognitive abilities as potential mediators, including lower level capacities like processing speed. Although performance on EF tasks depends on these abilities and thus likely captures the variance associated with them, it is not possible to rule out a specific SES-related deficit without explicit model testing. Other high-level processes related to cognitive self regulation (e.g., metacognition) also deserve empirical attention (Roebers, 2017).

A final limitation of our study is that it is not capable of differentiating whether individual differences in executive function influence performance on academic achievement tests via proximal or distal mechanisms. Because we measured EF more than two years prior to assessing academic achievement, it is possible that EF associations with achievement are due to (a) the influence of EF on cumulative learning during the intervening period, (b) the influence of EF on cognitive performance on the day of achievement testing, or (c) some combination of the two. Future research should assess EF and academic achievement at multiple time points to allow for more rigorous evaluation of the temporal dynamics of the association.

Despite these limitations, our findings reinforce a growing literature indicating that socioeconomic disparities in executive function contribute to the SES gap in academic achievement (Lawson

et al., 2017). What can be done to support the learning of children from disadvantaged backgrounds struggling with the executive function demands of the classroom? To date, most efforts to address this question have adopted one of two complementary approaches: training EF or accommodating instruction to the EF capacity of the learner (Cowan, 2014). Broad support exists for the logic model of interventions targeting EF improvement as a pathway to boosting later academic achievement (Bierman & Torres, 2016). That is, investments in EF skill development during childhood, when plasticity is likely at its highest, may pay dividends in academic achievement gains for years afterward. Although some evidence suggests that training can improve children's performance on EF tasks (e.g., attentional control, working memory, inhibiting irrelevant information; Diamond & Lee, 2011; Raver et al., 2011), most experimental research evaluating the efficacy of EF interventions for improving academic achievement has been conducted with small, clinical samples and has shown mixed results (Bergman Nutley & Söderqvist, 2017; Cowan, 2014; Rabipour & Raz, 2012). More definitive evidence of intervention efficacy is needed from large-sample trials of typically developing school-age children before limited school resources are allocated to such training programs.

A complementary approach to addressing cognitive barriers to learning is to adjust instructional practices and materials to meet the needs of the learner. Research grounded in cognitive load theory has demonstrated that traditional instruction of domain-specific concepts and skills places demands on working memory capacity that exceed the limits of many typically developing children (Paas, Renkl, & Sweller, 2003; Sweller, 2016). Recognizing this working memory constraint on learning, cognitive load theory has proposed modifications to instructional design that reduce cognitive load by limiting the number of items required to be processed at a given time. For instance, experimental evidence demonstrates that learning is improved when children are asked to study 'worked examples' rather than solving equivalent problems themselves, which overtax working memory (Sweller, 2011). Similarly, instructional practices requiring students to split attention between multiple sources of information, or to attend to redundant information, impede learning by placing unnecessary demands on working memory (Sweller, 2011).

Alloway (2006) provided several practical suggestions for modifying classroom practices to support children with poor working memory function based on a careful analysis of their most prevalent points of failure in classroom learning activities. For instance, given that children with poor working memory often fail to complete classroom activities simply because they forget what to do next, teachers can increase the odds of successful activity completion by frequently repeating clear, step-by-step instructions and asking children to repeat them aloud. To help children succeed in activities with the most challenging working memory demands, educators can provide training and repeated practice with the use of memory aids like unifix cubes, number lines, and lists of common words. Perhaps most importantly, children can be taught metacognitive strategies for coping with their working memory failures, including asking for forgotten information and engaging in positive self-talk to persist even when they fail.

To make progress reducing the SES-achievement gap, we must identify and address the specific barriers to learning and achievement faced by children from disadvantaged backgrounds. By identifying mediators of SES differences in performance on high stakes standardized testing, we hope this study further motivates and informs efforts by educational stakeholders to nurture the development of all children and adolescents, regardless of social class.

SOFTWARE

We analyzed our data and generated this fully reproducible report using R (Version 3.6.2; R Core Team, 2019) and the R-packages *apaTables* (Version 2.0.5; Stanley, 2018), *citr* (Version 0.3.2; Aust, 2018), *DiagrammeR* (Version 1.0.1; Iannone, 2019), *dplyr* (Version 0.8.3; Wickham, François, Henry, & Müller, 2019), *ggplot2* (Version 3.2.1; Wickham, 2016), *Hmisc* (Version 4.3.0; Harrell Jr, Charles Dupont, & others., 2019), *knitr* (Version 1.26; Xie, 2015), *lavaan* (Version 0.6.5; Rosseel, 2012), *papaja* (Version 0.1.0.9842; Aust & Barth, 2018), and *psych* (Version 1.8.12; Revelle, 2018).

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ENDNOTE

[1] We acknowledge that the factor loading for the Response Inhibition variable is weak. Nonetheless, we include the indicator in our model in order to maximize the comprehensiveness of our latent EF variable. We believe this decision is justified because the overall fit of the model is strong and latent variable models account for measurement errors of specific indicators. However, to ensure that model results were not biased by the inclusion of this variable, we re-tested each of the reported models with Response Inhibition omitted. Although specific parameter estimates varied slightly, the pattern of findings (including significance vs. non-significance of effects) was unchanged.

REFERENCES

Albert, D., & Steinberg, L. (2011). Age differences in strategic planning as indexed by the tower of London. *Child Development*, *82*(5), 1501–1517. https://doi.org/10.1111/j.1467-8624.2011.01613.x

Alloway, T. P. (2006). How does working memory work in the classroom? *Educational Research and Reviews*, *1*(4), 134–139.

Aust, F. (2018). Citr: 'RStudio' add-in to insert markdown citations. Retrieved from https://CRAN.R-project.org/package=citr

Aust, F., & Barth, M. (2018). papaja: Create APA manuscripts with R Markdown. Retrieved from https://github.com/crsh/papaja

Berg, K., & Byrd, D. (2002). The tower of London spatial problem-solving task: Enhancing clinical and research implementation. *Journal of Clinical and Experimental Neuropsychology*, *24*(5), 586–604. https://doi.org/10.1076/jcen.24.5.586.1006

Bergman Nutley, S., & Söderqvist, S. (2017). How is working memory training likely to influence academic performance? Current evidence and methodological considerations. *Frontiers in Psychology*, *8*, https://doi.org/10.3389/fpsyg.2017.00069

Beron, K., & Farkas, G. (2004). Oral language and reading success: A structural equation modeling approach. *Structural Equation Modeling*, *11*, 110–131. https://doi.org/10.1207/S15328007SEM1101_8

Best, J. R., Miller, P. H., & Naglieri, J. A. (2011). Relations between executive function and academic achievement from ages 5 to 17 in a large, representative national sample. *Learning and Individual Differences*, *21*(4), 327–336. https://doi.org/10.1016/j.lindif.2011.01.007

Bierman, K. L., & Torres, M. (2016). Promoting the development of executive functions through early education and prevention programs. In J. A. Griffin, P. McCardle, & L. S. Freund (Eds.), *Executive function in preschool-age children: Integrating measurement, neurodevelopment, and translational research* (pp. 299–326). Washington, D.C.: American Psychological Association. https://doi.org/10.1037/14797-014

Blair, C. B., & Razza, R. P. (2007). Relating effortful control, executive function, and false belief understanding to emerging math and literacy ability in kindergarten. *Child Development*, *78*(2), 647–663. https://doi.org/10.1111/j.1467-8624.2007.01019.x

Bornstein, M. H., & Putnick, D. L. (2019). *The Architecture of the Child Mind: G, Fs, and the Hierarchical Model of Intelligence* (1 edn). New York, NY: Routledge.

Bradley, R., & Corwyn, R. (2002). Socioeconomic status and child development. *Annual Review of Psychology*, *53*, 371–399. https://doi.org/10.1146/annurev.psych.53.100901.135233

Brock, L., Rimm-Kaufman, S., Nathanson, L., & Grimm, K. (2009). The contributions of 'Hot'and 'Cool' executive function to children's academic achievement, learning-related behaviors, and engagement in kindergarten. *Early Childhood Research Quarterly*, *24*, 337–349. https://doi.org/10.1016/j.ecresq.2009.06.001

Brooks-Gunn, J., & Duncan, G. (1997). The effects of poverty on children. *The Future of Children*, 55–71. https://doi.org/10.2307/1602387

Bull, R., Espy, K. A., & Wiebe, S. A. (2008). Short-term memory, working memory, and executive functioning in preschoolers: Longitudinal predictors of mathematical achievement at age 7 years. *Developmental Neuropsychology*, *33*(3), 205–228. https://doi.org/10.1080/87565640801982312

Casey, B., Getz, S., & Galvan, A. (2008). The adolescent brain. *Developmental Review*, *28*, 62–77. https://doi.org/10.1016/j.dr.2007.08.003

Chein, J., & Morrison, A. (2010). Expanding the mind's workspace: Training and transfer effects with a complex working memory span task. *Psychonomic Bulletin Review*, *17*, 193–199. https://doi.org/10.3758/PBR.17.2.193

Cowan, N. (2014). Working memory underpins cognitive development, learning, and education. *Educational Psychology Review*, *26*(2), 197–223. https://doi.org/10.1007/s10648-013-9246-y

Crook, S. R., & Evans, G. W. (2014). the role of planning skills in the income-achievement gap. *Child Development*, *85*(2), 405–411. https://doi.org/10.1111/cdev.12129

Cumming, G. (2014). The new statistics: Why and how. *Psychological Science*, *25*(1), 7–29. https://doi.org/10.1177/0956797613504966

Dahl, G., & Lochner, L. (2012). The impact of family income on child achievement: Evidence from the earned income tax credit. *The American Economic Review*, *102*(5), 1927–1956. https://doi.org/10.1257/aer.102.5.1927

Diamond, A., & Lee, K. (2011). Interventions shown to aid executive function development in children 4 to 12 years old. *Science (New York, N.Y.)*, *333*(6045), 959–964. https://doi.org/10.1126/science.1204529

Dilworth-Bart, J. (2012). Does executive function mediate SES and home quality associations with academic readiness? *Early Childhood Research Quarterly*, *27*, 416–425. https://doi.org/10.1016/j.ecresq.2012.02.002

Ditlevsen, S., Christensen, U., Lynch, J., Damsgaard, M., & Keiding, N. (2005). The mediation proportion: A structural equation approach for estimating the proportion of exposure effect on outcome explained by an intermediate variable. *Epidemiology*, *16*, 114–120. https://doi.org/10.1097/01.ede.0000147107.76079.07

Duncan, G. J., Dowsett, C. J., Claessens, A., Magnuson, K., Huston, A. C., Klebanov, P., … Japel, C. (2007). School readiness and later achievement. *Developmental Psychology*, *1428*, 43. https://doi.org/10.1037/0012-1649.43.6.1428

Duyme, M., Dumaret, A. C., & Tomkiewicz, S. (1999). How can we boost IQs of "Dull Children"? a late adoption study. *Proceedings of the National Academy of Sciences of the United States of America*, *96*(15), 8790–8794. https://doi.org/10.1073/pnas.96.15.8790

Evans, G. W. (2004). The environment of childhood poverty. *American Psychologist*, *59*, 77–92. https://doi.org/10.1037/0003-066X.59.2.77

Farah, M. J., Shera, D. M., Savage, J. H., Betancourt, L., Giannetta, J. M., Brodsky, N. L., … Hurt, H. (2006). Childhood poverty: Specific associations with neurocognitive development. *Brain Research*, *1110*(1), 166–174. https://doi.org/10.1016/j.brainres.2006.06.072

Farkas, G., & Beron, K. (2004). The detailed age trajectory of oral vocabulary knowledge: Differences by class and race. *Social Science Research*, *33*(3), 464–497. https://doi.org/10.1016/j.ssresearch.2003.08.001

Fitzpatrick, C., McKinnon, R., Blair, C. B., & Willoughby, M. (2014). Do preschool executive function skills explain the school readiness gap between advantaged and disadvantaged children? *Learning and Instruction*, *30*, 25–31.

Gottfried, A., Bathurst, K., Guerin, D., Parramore, M., In, M., & Mahwah, N. (2003). Socioeconomic Status in Children's Development and Family Environment: Infancy through Adolescence. In B. R. H. Bradley (Ed.) *Socioeconomic Status Parenting and Child Development Pp Lawrence Erlbaum Associates* (pp. 189–207). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Hackman, D., Farah, M. J., & Meaney, M. (2010). Socioeconomic status and the brain: Mechanistic insights from human and animal research. *Nature Reviews Neuroscience*, *651*, 11. https://doi.org/10.1038/nrn2897

Harrell, F. E. Jr, Charles Dupont, & others. (2019). Hmisc: Harrell miscellaneous. Retrieved from https://CRAN.R-project.org/package=Hmisc

Hart, B., & Risley, T. (2003). The early catastrophe: The 30 million word gap by age 3. *American Educator*, *27*, 4–9.

Haveman, R., & Wolfe, B. (1995). The determinants of children's attainments: A review of methods and findings. *Journal of Economic Literature*, *33*, 1829–1878.

Heaton, R. K., & Pendleton, M. G. (1981). Use of neuropsychological tests to predict adult patients' everyday functioning. *Journal of Consulting and Clinical Psychology*, *49*(6), 807–821. https://doi.org/10.1037/0022-006X.49.6.807

Hoff, E. (2003). The specificity of environmental influence: Socioeconomic status affects early vocabulary development via maternal speech. *Child Development*, *74*(5), 1368–1378. https://doi.org/10.1111/1467-8624.00612

Hoff, E., & Tian, C. (2005). Socioeconomic status and cultural influences on language. *Journal of Communication Disorders*, *38*(4), 271–278. https://doi.org/10.1016/j.jcomdis.2005.02.003

Iannone, R. (2019). DiagrammeR: Graph/network visualization. Retrieved from https://github.com/rich-iannone/DiagrammeR

Krapohl, E., Hannigan, L. J., Pingault, J.-B., Patel, H., Kadeva, N., Curtis, C., … Plomin, R. (2017). Widespread covariation of early environmental exposures and trait-associated polygenic variation. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(44), 11727–11732. https://doi.org/10.1073/pnas.1707178114

Kurdek, L., & Sinclair, R. (2001). predicting reading and mathematics achievement in fourth-grade children from kindergarten readiness scores. *Journal of Educational Psychology*, *451*, 93. https://doi.org/10.1037/0022-0663.93.3.451

Last, B. S., Lawson, G. M., Breiner, K., Steinberg, L., & Farah, M. J. (2018). Childhood socioeconomic status and executive function in childhood and beyond. *PLoS ONE*, *13*(8), e0202964. https://doi.org/10.1371/journal.pone.0202964

Lawson, G., & Farah, M. J. (2017). Executive function as a mediator between SES and academic achievement throughout childhood. *International Journal of Behavioral Development*, *41*, 94–104. https://doi.org/10.1177/0165025415603489

Lawson, G., Hook, C., & Farah, M. J. (2017). A meta-analysis of the relationship between socioeconomic status and executive function performance among children. *Developmental Science*, *21*, e12529. https://doi.org/10.1111/desc.12529

Lee, C., & Solon, G. (2009). Trends in intergenerational income mobility. *The Review of Economics and Statistics*, *91*(4), 766–772. https://doi.org/10.1162/rest.91.4.766

Lonigan, C., Burgess, S., & Anthony, J. (2000). Development of emergent literacy and early reading skills in preschool children: Evidence from a latent-variable longitudinal study. *Developmental Psychology*, *36*(5), 596–613. https://doi.org/10.1037/0012-1649.36.5.596

Luna, B., Padmanabhan, A., & O'Hearn, K. (2010). What has fMRI told us about the development of cognitive control through adolescence? *Brain and Cognition*, *72*(1), 101–113. https://doi.org/10.1016/j.bandc.2009.08.005

Mazzocco, M. M. M., & Kover, S. T. (2007). A Longitudinal assessment of executive function skills and their association with math performance. *Child Neuropsychology: A Journal on Normal and Abnormal Development in Childhood and Adolescence*, *13*(1), 18–45. https://doi.org/10.1080/09297040600611346

Mercy, J., & Steelman, L. (1982). Familial influence on the intellectual attainment of children. *American Sociological Review*, *47*, 532–542. https://doi.org/10.2307/2095197

Mezzacappa, E. (2004). Alerting, orienting, and executive attention: Developmental properties and sociodemographic correlates in an epidemiological sample of young, urban children. *Child Development*, *75*(5), 1373–1386. https://doi.org/10.1111/j.1467-8624.2004.00746.x

Nesbitt, K., Baker-Ward, L., & Willoughby, M. (2013). Executive function mediates socio-economic and racial differences in early academic achievement. *Early Childhood Research Quarterly*, *28*, 774–783. https://doi.org/10.1016/j.ecresq.2013.07.005

NICHD Early Child Care Research Network. (2003). Do childrens attention processes mediate the link between family predictors and school readiness? *Developmental Psychology*, *39*, 581–593.

Nittrouer, S. (1996). The relation between speech perception and phonemic awareness: Evidence from low-SES children and children with chronic OM. *Journal of Speech and Hearing Research*, *39*(5), 1059–1070. https://doi.org/10.1044/jshr.3905.1059

Noble, K. G., McCandliss, B. D., & Farah, M. J. (2007). Socioeconomic gradients predict individual differences in neurocognitive abilities. *Developmental Science*, *10*(4), 464–480. https://doi.org/10.1111/j.1467-7687.2007.00600.x

Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist*, *38*(1), 1–4. https://doi.org/10.1207/S15326985EP3801_1

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

R Core Team. (2019). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Rabipour, S., & Raz, A. (2012). Training the brain: Fact and fad in cognitive and behavioral remediation. *Brain and Cognition*, *79*(2), 159–179. https://doi.org/10.1016/j.bandc.2012.02.006

Raver, C. C., Jones, S. M., Li-Grining, C., Zhai, F., Bub, K., & Pressler, E. (2011). CSRP's Impact on Low-Income Preschoolers' preacademic skills: Self-regulation as a mediating mechanism. *Child Development*, *82*(1), 362–378. https://doi.org/10.1111/j.1467-8624.2010.01561.x

Reardon, S., In, R., & York, N. (2011). The widening academic achievement gap between the rich and the poor: New evidence and possible explanations. In M. G. Duncan (Ed.), *Whither opportunity rising inequality and the uncertain life chances of lowincome children* (pp. 91–113). New Russell: Sage Foundation Press.

Revelle, W. (2018). *Psych: Procedures for psychological, psychometric, and personality research*. Evanston, IL: Northwestern University. Retrieved from https://CRAN.R-project.org/package=psych

Roebers, C. M. (2017). Executive function and metacognition: Towards a unifying framework of cognitive self-regulation. *Developmental Review*, *45*, 31–51. https://doi.org/10.1016/j.dr.2017.04.001

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36. Retrieved from http://www.jstatsoft.org/v48/i02/

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H.(2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research*, *8*(2), 23–74.

Schmitt, S., McClelland, M., Tominey, S., & Acock, A. (2015). Strengthening school readiness for head start children: Evaluation of a self-regulation intervention. *Early Childhood Research Quarterly*, *30*, 20–31. https://doi.org/10.1016/j.ecresq.2014.08.001

Shallice, T. (1982). Specific Impairments of Planning. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *298*(1089), 199–209. https://doi.org/10.1098/rstb.1982.0082

St Clair-Thompson, H. L., & Gathercole, S. E. (2006). Executive functions and achievements in school: Shifting, updating, inhibition, and working memory. *Quarterly Journal of Experimental Psychology*, *59*(4), 745–759. https://doi.org/10.1080/17470210500162854

Stanley, D. (2018). ApaTables: Create american psychological association (apa) style tables. Retrieved from https://CRAN.R-project.org/package=apaTables

Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, *18*, 643–662. https://doi.org/10.1037/h0054651

Sweller, J.(2011). CHAPTER TWO - Cognitive Load Theory. In J. P. Mestre, & B. H. Ross (Eds.), *Psychology of Learning and Motivation* (Vol. *55*, pp. 37–76). Academic Press. https://doi.org/10.1016/B978-0-12-387691-1.00002-8

Sweller, J. (2016). Working memory, long-term memory, and instructional design. *Journal of Applied Research in Memory and Cognition*, *5*(4), 360–367. https://doi.org/10.1016/j.jarmac.2015.12.002

Thompson-schill, S. L., Jonides, J., Marshuetz, C., Smith, E. E., D'esposito, M., Kan, I. P., … Swick, D. (2002). Effects of frontal lobe damage on interference effects in working memory. *Cognitive, Affective & Behavioral Neuroscience*, *2*(2), 109–120. https://doi.org/10.3758/CABN.2.2.109

Waber, D. P., De moor, C., Forbes, P. W., Almli, C. R., Botteron, K. N., Leonard, G., … Rumsey, J.; Brain Development Cooperative Group. (2007). The NIH MRI study of normal brain development: Performance of a population based sample of healthy children aged 6 to 18 years on a neuropsychological battery. *Journal of the International Neuropsychological Society*, *13*(5), 729–746. https://doi.org/10.1017/S1355617707070841

Welsh, J. A., Nix, R. L., Blair, C. B., Bierman, K. L., & Nelson, K. E. (2010). The development of cognitive skills and gains in academic school readiness for children from low-income families. *Journal of Educational Psychology*, *102*(1), 43–53. https://doi.org/10.1037/a0016738

Wickham, H. (2016). *Ggplot2: Elegant graphics for data analysis*. New York: Springer-Verlag. Retrieved from https://ggplot2.tidyverse.org

Wickham, H., François, R., Henry, L., & Müller, K. (2019). Dplyr: A grammar of data manipulation. Retrieved from https://CRAN.R-project.org/package=dplyr

Woodcock, R. W., McGrew, K. S., & Mather, N. (2001). *Woodcock-Johnson III Battery* . Itasca, IL: Riverside Publishing Company.

Woods, S. P., Delis, D. C., Scott, J. C., Kramer, J. H., & Holdnack, J. A. (2006). The california verbal learning test – second edition: Test-retest reliability, practice effects, and reliable change indices for the standard and alternate forms. *Archives of Clinical Neuropsychology*, *21*(5), 413–420. https://doi.org/10.1016/j.acn.2006.06.002

Xie, Y. (2015). *Dynamic documents with R and knitr* (2nd edn.). Boca Raton, Florida: Chapman; Hall/CRC. Retrieved from https://yihui.name/knitr/

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

How to cite this article: Albert WD, Hanson JL, Skinner AT, et al. Individual differences in executive function partially explain the socioeconomic gradient in middle-school academic achievement. *Dev Sci.* 2020;23:e12937. https://doi.org/10.1111/desc.12937