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RESEARCH ARTICLE

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The relationship between cognitive enrichment and cognitive control: A systematic investigation of environmental influences on development through socioeconomic status

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Abstract

We measured the impact of socioeconomic status (SES) on cognitive processes. We examined cognitive control, specifically working memory (WM), in a sample of *N* = 141 7- to 17-year-olds using rule-guided behavior tasks. Our hypothesis is based on computational modeling data that suggest that the development of flexible cognitive control requires variable experiences in which to implement rule-guided action. We found that not all experiences that correlated with SES in our sample impacted task performance, and not all experiential variables that impacted performance were associated with SES. Of the experiential variables associated with task performance, only cognitive enrichment opportunities worked indirectly through SES to affect WM as tested with rule-guided behavior tasks. We discuss the data in the context of necessary precision in SES research.

KEYWORDS
cognitive control, cognitive enrichment, socioeconomic status, working memory

1 | INTRODUCTION

Socioeconomic status (SES) reflects the social standing of a family and is operationalized as a composite of parent education, occupation, and income (McLoyd, 1998). There is a well-documented SES achievement gap. For example, across the entire income spectrum, children from higher income communities are substantially more likely to attend college (Chetty, Hendren, Kline & Saez, 2014). We focus this investigation on cognitive control and specifically updating rules for action into working memory (WM). Family SES has been linked to individual differences in prefrontal cortex (PFC)-dependent executive functions or cognitive control, often interchangeable terms that describe WM, set shifting, and inhibitory skills (Amso, Haas, McShane & Badre, 2014; Lawson, Hook & Farah, 2017; Sheridan, Fox, Zeanah, McLaughlin, & Nelson, 2012) . In turn, cognitive control is critical to academic achievement outcomes (Lawson & Farah, 2017). Our hypothesis is that SES differences in the development of cognitive control may arise from more numerous and variable opportunities for building stable, abstract rule representations for flexible behavior in higher SES homes.

Cognitive control supports flexible thought and action. This flexibility involves PFC-governed rule-guided behavior (Badre & D'Esposito, 2007; Badre, Hoffman, Cooney & D'Esposito, 2009; Chatham, Frank & Badre, 2014). Consider a mother and her child building a structure out of blocks. The toddler can respond correctly to a mother asking the toddler to retrieve a square block from among other square blocks. In this scenario, the action would be considered a response to a "first-order" rule, where there is only one level of contingency between the goal and the response. The child simply needs to update the request into WM for action selection. The task is made more difficult if the blocks varied by two dimensions, for example, both shape and color (red/blue circular blocks and red/blue square blocks). Here, retrieving the correct square object may depend on a "second-order" rule. The mother may say to the child, "I need a square shape to fit in this hole. Can you please give me the blue one?" This is an example of a rule hierarchy, where the shape rule hierarchically governs which blue object to retrieve. In this case, the child must update the shape rule (square) into WM, which immediately eliminates all the circular blocks for action selection, and then must update the color rule (blue) in order to select among the red and blue square blocks to give to mother.

Rule-guided behavior of this type has long been the focus of study in cognitive control research, as it supports complex contingent action selection (Badre & D'Esposito, 2007; Badre et al., 2009; Chatham et al., 2014; Ranti, Chatham & Badre, 2015), learning and generalization (Badre & Frank, 2012; Badre, Kayser & D'Esposito, 2010; Botvinick, 2008; Collins & Frank, 2013; Frank & Badre, 2012), decision making (Badre, Doll, Long & Frank, 2012), fluid reasoning (Bunge, 2004; Speed, 2010), and planning (Koechlin, Corrado, Pietrini & Grafman, 2000). This host of skills is key to flexible thought and action and academic success. For example, Crook and Evans (2014) found that early planning ability is a mediator for the income–achievement gap in math.

From a mechanistic perspective, success in cognitive control requires both updating rules into WM (WM updating) and being able to maintain (WM maintenance) these rules in WM in the presence of competing alternatives for action selection (Amso et al., 2014; Badre & D'Esposito, 2007; Chatham & Badre, 2015; Unger, Ackerman, Chatham, Amso, & Badre, 2016). Both mechanisms become increasingly difficult as rule-order increases. Recent work (Amso et al., 2014; Unger et al., 2016) used three tasks, parametrically increasing in rule-order, to show that developmental improvements in rule-guided behavior in the transition from late childhood to adolescence were linked to the development in WM updating. Figure 1 shows the Response and Feature tasks used here and in Amso et al. (2014). The logic of the tasks is (a) to increase the demand on WM updating and maintenance by going from Block 1 to Block 2 (Figure 1) and (b) to increase WM maintenance only at any single rule-order by going from Block 2 to Block 4. While increasing items in WM for maintenance was costly for all participants, there was no additional cost with development when WM maintenance was isolated at any rule-order.

In an exploratory analysis, Amso et al. (2014) found that higher SES (composite of income, occupation, and education) was associated with the more efficient development of WM updating, as measured by smaller costs in updating higher order rules into WM for action, in the transition from childhood to adolescence. Here, we report data from an investigation of the same Response and Feature

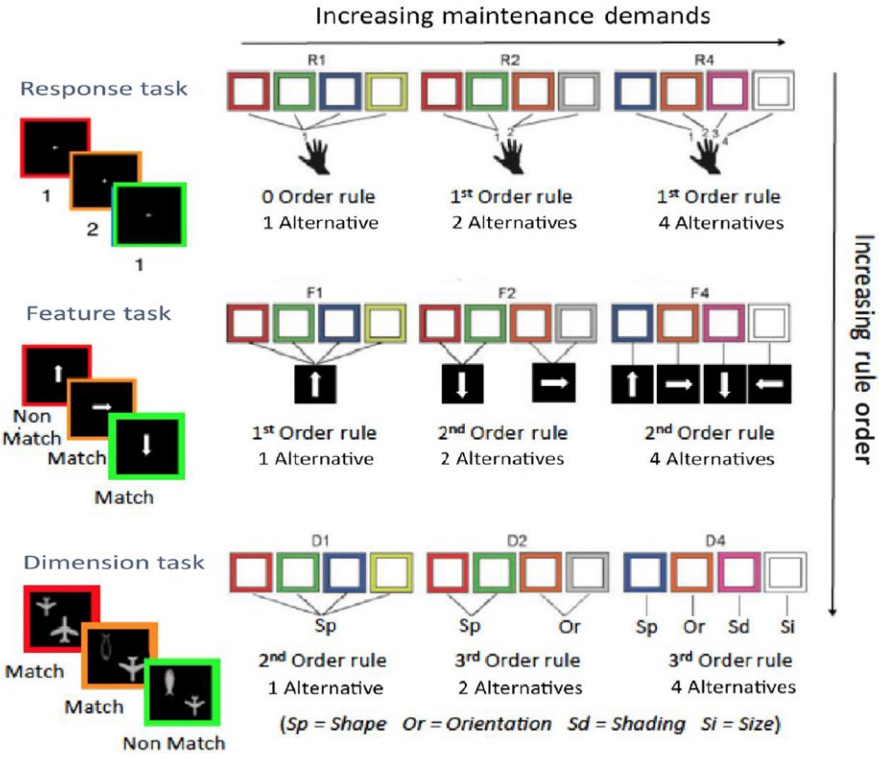

FIGURE 1 Illustrates three tasks that parametrically manipulate working memory (WM) updating (through rule-order) and WM maintenance (through the number of alternatives maintained in WM for action). Across all tasks, performance costs on the 1 versus 2 blocks measure the cost of updating higher order rules into working memory for action as well as increasing WM maintenance, whereas performance on the 2 versus 4 blocks isolates the cost of WM maintenance. The Response task R1 block is a zero-order rule. A single response is correct for any stimulus. Correct response on R2 and R4 blocks requires updating of first-order rules into WM, where the color of the box indicates the correct response. The R4 block maintains the same first-order rule structure as R2, but adds additional alternatives for WM maintenance. The Feature and Dimension tasks follow the same logic. The Feature task F1 is a first-order rule block, while F2 and F4 are second-order blocks. Participants are instructed to determine whether the arrow is pointing in the right direction given the box color. Among the second-order F2 and F4 blocks, only the number of competing alternatives for WM maintenance (from 2 to 4) is increased. The Dimension Task D1 block is a second-order block, whereas D2 and D4 are third-order rule blocks. Participants are instructed to use the box color to then select a dimension (shape, orientation) to then match to an arrow direction. D2 and D4 are both third-order rule blocks, but D4 increases only the number of competing alternatives maintained in WM for action

tasks used in Amso et al. (2014) and with the addition of a third-order rule task called the Dimension task. Using all three tasks is methodologically important. Lawson, Camins, et al. (2017) and Lawson, Hook, et al. (2017) recently conducted a meta-analysis of the impact of SES on executive functions and found mixed results and only a medium effects size. Appropriateness of the task for the sample age group, and also for the construct under investigation, likely plays a role in these mixed results. Our previous work showed that accuracies on the Response task are high even in young children (Amso et al., 2014) and that the Dimension task can be challenging for even adolescents and adults (Unger et al., 2016). Thus, we incorporate all three rule-guided behavior tasks (first-order Response, second-order Feature, and third-order Dimension, Figure 1) into this investigation to ensure that we have sufficient variability in performance to explore SES.

Mechanistically, the formation of stable rule representations for action arises from frontostriatal reinforcement learning mechanisms during childhood (Snyder & Munakata, 2010; Werchan, Collins, Frank, & Amso, 2015, 2016). Computational models of the formation of these representations have emphasized the variability of experience as key determining factors. Rougier, Noelle, Braver, Cohen and O'Reilly (2005) tested how such flexibility develops and the types of inputs necessary for this development. They tested their PFC models, that incorporated the WM updating and WM maintenance mechanisms discussed here, on a variety of tasks (ordering, matching, stimulus response) that all required a single rule structure for successful response along a stimulus dimension (i.e., color, size, and shape). They found that the PFC develops strong abstract rule representations, that are common over specific situations, only when exposed to variable experience with a range of tasks. Once the patterns of activity were learned, the model was able to bypass having to learn a new set of connection strengths by searching these patterns for action when confronted with a novel situation. In the same way, the learning opportunities and variable contexts in which to implement rule-guided action may vary along family SES.

Thus, we reasoned that if the goal is to build a flexible and adaptive behavioral repertoire, one must be able to learn abstract rule representations from variable experiences. Data have shown that cognitively stimulating materials and experiences are less common in low SES homes (Bradley, Corwyn, McAdoo & García Coll, 2001; Hart & Risley, 1995). Higher SES homes have more access to enriching resources and variable opportunities in which to implement rule-guided behavior. These may take the form of greater language complexity, education quality, travel experiences, specialized sports team membership, books and toys, music lessons, etc. (e.g., Conger & Donnellan, 2007; Hackman, Gallop, Evans & Farah, 2015; McLaughlin, Sheridan & Nelson, 2017). Taken together with the PFC model predictions (Rougier et al., 2005), these data lead us to predict that SES differences in the development of rule-guided behavior specifically, and WM more broadly, may arise from more numerous and variable opportunities for building stable, abstract rule representations in higher SES homes. Indeed, complexity of spoken language in the home, participation in literacy activities with parents, and access to digital media have all been shown to be positive experiential mediators of the relation between cognitive control and SES (Lipina et al., 2013; Sheridan, Sarsour, Jutte, D'Esposito, & Boyce, 2012).

It is important to note that SES effects on PFC structure and function are a result of both positive enrichment in high SES homes and exposure to stressful experiences in low SES homes (Conger & Donnellan, 2007; Johnson, Riis & Noble, 2016; Ursache & Noble, 2016). However, our goal is to understand how SES across a wide income range impacts WM, not how the biological embedding of stress impacts WM. A critical distinction is that stress and enrichment act through different mechanisms to shape development (Amso & Lynn, 2017; Conger & Donnellan, 2007; Johnson et al., 2016; Lawson, Camins, et al., 2017; Lawson, Hook, et al., 2017; McLaughlin & Sheridan, 2016; McLaughlin et al., 2017; Sheridan, Peverill, Finn, & McLaughlin, 2017; Ursache & Noble, 2016) . When incorporating the adversities more common in poverty, there is little doubt that stresses acts to shape outcomes. Yet even in children experiencing adversity, McLaughlin and Sheridan (2016) have argued that, depending on the type of adversity, cognitive development and emotional development are shaped by mechanisms other than stress, including through learning disruptions.

However, the effects of SES on development tend to not be specific to the low end of the SES range. For example, many of the effects on PFC structure and function are evident across the SES spectrum and are not unique to children growing up in poverty or in low SES homes (Gianaros et al., 2007; Noble, Engelhardt, et al., 2015; Noble, Houston, et al., 2015; Piccolo, Merz, He, Sowell & Noble, 2016; Sarsour et al., 2011). The SES achievement gap is also not specific to children living in poverty. Across *the entire income spectrum*, children from higher income communities are more likely to go to college (Chetty et al., 2014). This means that a child from a low-income home is less likely attend college compared to a child from a wealthy home, who is less likely to go to college than a child from an extremely wealthy home.

Extensive literature shows that adverse experiences impact the developing system through the biological embedding of stress (McEwen, 1998, 2002, 2008) and are measurable in populations with extreme poverty and adversity through changes in cortisol levels (Blair et al., 2011; Evans & English, 2002; Lupien, King, Meaney & McEwen, 2000; Tarullo & Gunnar, 2006). Studies that have examined cortisol level differences due to stress have found minimal evidence that cortisol varies across the entire spectrum of SES (Cutuli, Wiik, Herbers, Gunnar & Masten, 2010; Dowd, Simanek & Aiello, 2009; West, Sweeting, Young, & Kelly, 2010). Thus, the effects of adversity and SES are correlated in the lowest end of the income spectrum; however, the effects of SES persist beyond this lowest income range. This suggests that children in the lowest SES range are more likely to have multiple risk factors shaping their development. Taking these distinctions into account, we assert that this investigation is specifically focused on mechanisms of SES function and not the additive effects of adversities more common in poverty.

Here, we examined the relationship between SES and cognitive control in a sample of children from a wide range of SES backgrounds. All families completed the Home Observation Measurement of the Environment-Short Form (HOME-SF), a laboratory version of the measures collected with the original HOME inventory (Bradley & Caldwell, 1984; Bradley et al., 1992). We chose the HOME-SF because it includes various questions about opportunities for variable cognitive stimulation in the child's environment including as age appropriate, opportunities for playing musical instrument, going to museums, reading books, lessons for dance, art, drama, TV watching, book reading, chore requirements, and quality of interaction with parent figures. We additionally customized HOME-SF subscales in this investigation to measure cognitive, emotional, and parenting style experiences that have been shown to vary by SES and/or impact cognitive control in previous work (Blair et al., 2011; Bradley et al., 2001; Conger & Donnellan, 2007; Hackman et al., 2015; Lipina et al., 2013; Sheridan, Sarsour et al., 2012). Finally, we incorporated an assessment of negative experiences to which a participant has recently been exposed. The Life Events Checklist (LEC, Johnson & McCutcheon, 1980) has been validated with other measures that assess trauma history (Gray, Litz, Hsu & Lombardo, 2004). Because we do not expect an effect of the LEC on cognitive control, we also added an IQ assessment where results would be expected to associate with LEC and stressful events (Nisbett et al., 2012). This strategy ensures that there is sufficient variability in LEC outcomes to find an effect if one were present.

We focused our investigation on the transition from childhood to adolescence, a time of great change in cognitive control (Montez, Calabro, & Luna, 2017; Rosen, Sheridan, Sambrook, Meltzoff & McLaughlin, 2018; Siffredi et al., 2017; Wendelken, Ferrer, Whitaker, & Bunge, 2015) . This is a time marked by changes in peer relations, increased independence, and academic demand. The developing child is confronted with increasingly complex contexts in which to implement rule-guided behavior, as well as a larger number of competing options to choose from. It follows that the ability of the developing system to meet these challenges is key to mental and physical health and wellness outcomes.

2 | METHOD

2.1 | Participants

Our sample included $N = 141$ 7- to 17-year-old children and adolescents (Table 1). Of these, 21% ($N = 29$) were Black or African American and 79% ($N = 112$) were Caucasian, with 16% ($N = 23$) being of Hispanic ethnicity. Participants were recruited through local advertisements as well as through recruitment in school districts with a high percentage of students that received free or reduced lunches. Prior to enrollment, we screened participants for a history of diagnosed psychiatric disorders, uncorrected visual or auditory impairments, or preterm birth. Families were compensated for their participation. Parents gave written and verbal informed consent and children provided assent. All participants had normal or corrected-to-normal vision and hearing. All passed the Ishihara test for color deficiency.

TABLE 1 Descriptive demographic statistics of sample

	Mean	Standard deviation	Range (min, max)	Skewness
Sex (% male)	55%			
Age in years	11.10	2.80	(7.0, 17.3)	0.39
Parent 1 Education in years	15.80	2.40	(8.0, 21)	−0.26
Parent 1 Occupational level[a]	3.60	0.91	(2, 5)	0.04
Income (in $1,000)	98.00	64.60	(6.6, 450)	2.20
Income-to-needs ratio	3.80	2.50	(0.7, 16.3)	1.96
HOME-SF cognitive stimulation	0.80	0.14	(0.31, 1.0)	−1.13
HOME-SF emotional	0.82	0.14	(0.18, 1.0)	−1.52
LEC # negative life events	1.99	3.47	(0, 26)	4.69
Woodcock–Johnson GIA	104.13	14.23	(60, 155)	0.46

Notes. GIA: General Intelligence Ability; HOME-SF: Home Observation for Measurement of the Environment-Short Form; LEC: Life Events Checklist.

[a] Parent occupational level coded using O*Net ratings available through the US Department of Labor on a scale of 1–5.

2.2 | Procedures

Participants completed two experimental sessions on two different days, separated by one to four weeks. In one session, they performed the Response and the Feature tasks. In the other session, they completed the Dimension task and the Woodcock–Johnson IQ test. The order of sessions was counterbalanced across participants, as was the order of tasks within a session. While participants completed the tasks, parents filled out demographic information. Of the total *N* = 141 participants, behavioral task reaction time (RT) data were reported in a subset of *N* = 59 in Unger et al. (2016) in an investigation establishing patterns of development of rule-guided behavior. None of the SES data analyses in this report were in Unger et al. (2016). Of the *N* = 141 participants tested, *N* = 114 contributed data to the Response task, *N* = 115 contributed full data to the Feature task, and *N* = 123 contributed data to the Dimension task. The remainder either failed to complete a task or did not return for one of the sessions.

2.3 | Rule-guided behavior tasks and dependent variables

Each Response, Feature, and Dimension task (Figure 1) included six training blocks (two blocks for each WM load condition) that were followed by six experimental blocks. Blocks were fully counterbalanced across participants. Blocks contained 33 trials for the Response task, 32 trials for the Feature task, and 25 trials for the Dimension task. Responses were recorded on a keyboard. Participants were instructed to go as fast as they could and to be as accurate as possible. During Feature and Dimension tasks, participants used index and middle finger of their dominant hand to make a response, while for the Response task, each finger of the dominant hand was assigned to one response key. Each of the two experimental sessions lasted between 1 and 1.5 hr. All participants were tested individually.

2.3.1 | Response task

On each trial, a colored square appeared in the middle of the computer screen on a black background for a maximum of 2 s until participants made a response. Trials were separated by a randomly jittered fixation interval of 0–2 s. Within a given block of trials, the response key was chosen based on the color of the square. There were three different block types, each of which included four colors that mapped onto one (R1 block), two (R2), or four (R4) different keys (see Figure 1). On *R1 blocks*, each of the four colors was assigned to the same response key. Since participants were not faced with a choice, this defined a zero-order rule with no competition between response alternatives. During R2 blocks, two colors mapped onto one response key, while the other two colors mapped onto a second response key. Hence, in order to select the correct response, participants had to use a first-order rule that involved a single-level decision over two response alternatives. On R4 blocks (also first-order), the four colors mapped onto four different keys such that participants were required to choose between four response alternatives.

2.3.2 | Feature task

Participants saw a colored square, with a white arrow inside, that pointed in one of four directions (up, down, left, and right). Trials followed the same procedure as in the Response task, except that the stimuli were presented for a maximum of 4 s. Analogous to the experimental logic of the Response task, trials were grouped into three alternate block types, each of which included four-color direction mappings that defined one (F1), two (F2), or four (F4) different target directions (see Figure 1). On F1 blocks, each color mapped onto the same target direction. Hence, participants had to follow a first-order rule by making single-level decisions over two response alternatives (match vs. nonmatch). By contrast, F2 and F4 blocks involved second-order rules requiring a two-level decision over two (F2) versus four (F4) alternatives that mapped a given direction onto a match versus nonmatch response (second level).

2.3.3 | Dimension task

On each trial, two objects were displayed inside a colored square. Participants were asked to press one of two response keys to indicate whether the objects matched along a certain dimension (shape, size, orientation, or shading). The object pairs were selected such that there were always two matching and two nonmatching dimensions. The relevant dimension was cued by the color of the square. The general trial procedure was the same as in the Feature task. On D1 blocks, each of the four colors was assigned to the same dimension (e.g., direction), so participants had to use a second-order rule that requires a decision on relations between features corresponding to the relevant dimension (e.g., "Is the first object pointing in the same direction as the second object?"). On D2 and D4 blocks, participants followed third-order rules that required them to arbitrate between two (D2) and four (D4) dimensions in order to select the correct second-order rule to make a match/nonmatch decision.

2.3.4 | Woodcock-Johnson III Tests of Cognitive Abilities (e.g., Woodcock, Mather, & Schrank, 2010)

We used the full standard battery to calculate a General Intellectual Ability (GIA) score, based on a weighted combination of all subtests.

2.4 | Demographic data collection and preprocessing

2.4.1 | SES demographic questionnaire

Parents reported the number of years of education they completed. Occupation was assessed on a scale of 1–5 using the O*Net rankings. O*Net was developed by the US Department of Labor/Employment and Training Administration as part of a nationally recognized database on occupational information. Annual household income was reported in dollars. Household income was used to calculate the

TABLE 2 Estimated factor-item loadings for the HOME-SF confirmatory factor analysis model

Factor	Cognitive enrichment	Routine	Parental closeness	Restrictive parenting	Parental monitoring	Supportive parenting
Item						
Child reads for fun	0.57					
Weekday hours spent watching TV	0.55					
Discuss TV programs with child	0.51					
Take child to performance	0.48					
Taken child to museum	0.39					
Weekend hours spent watching TV	0.39					
Number of books	0.35					
Musical instrument	0.30					
Receive daily newspaper	0.20					
Pick up after self		0.93				
Keep shared areas clean		0.87				
Make own bed		0.83				
Clean own room		0.60				
Help with chores		0.60				
Manage own time		0.20				
How close child feels 2nd caregiver			0.76			
Time spent with 2nd caregiver			0.67			
Outdoor time with 2nd caregiver			0.59			
How close child feels to you			0.41			
Bad grade response—punishment				0.83		
Bad grade response—lecture				0.61		
Tantrum/Angry response—grounding				0.47		
Tantrum/Angry response—chores				0.47		
Tantrum/Angry response—reduce privileges				0.44		
Tantrum/Angry response—reduce allowance				0.37		
Tantrum/Angry response—timeout				0.33		
Bad grade response—reduce privileges				0.32		
Bad grade response—grounding				0.29		
Bad grade response—help child with work					0.83	
Bad grade response—contact school					0.57	
Bad grade response—monitor activities					0.51	
Praised child to another adult last week						0.99
Shown child physical affection last week						0.92
Praised child in last week						0.21

Note. HOME-SF, Home Observation for Measurement of the Environment-Short Form.

income-to-needs ratio (i.e., income divided by the poverty threshold for an analogous family size).

2.4.2 | Home Observation for Measurement of the Environment-Short Form (HOME-SF) (Bradley & Caldwell, 1984; Bradley et al., 1992)

Several studies have demonstrated high reliability and construct validity for both the original HOME and HOME-SF instruments (Baker, Keck, Mott & Quinlan, 1993; Mott, 1994). The HOME-SF questionnaire was completed by the caregiver and offered two scores for Emotional Support and Cognitive Stimulation. We constructed finer subscales by grouping items in the HOME-SF that describe the child's environment with respect to material enrichment and opportunity and parenting behavior, as these have been shown to be different across SES homes and to impact cognitive control. See Fuligni, Han and Brooks-Gunn (2004) for a similar approach. Additional subscales used for the primary analyses were constructed by standardizing individual items, to account for differing response scales, summing those items and standardizing those summed scales. We performed a confirmatory factor analysis (CFA) of a custom 6-subscale structure of the HOME-SF. The CFA is described in detail in the Section 3. The HOME-SF CFA model included the following subscales: routine, cognitive enrichment, parental closeness, restrictive parenting, parental monitoring, and supportive parenting.

2.4.3 | Life Events Checklist Negative Events (Johnson & McCutcheon, 1980)

The LEC is a 46-item questionnaire that measures the occurrence of positive and negative life events for the child over the past 12 months, as reported by the caregiver. The questions ask the caregiver to indicate whether an event occurred and its perceived levels of stress/unpleasantness (4-point scale). There is also a place to write in experiences not indicated on the 46 items. In the present study, we used the cumulative sum of the number of negative life events reported from the LEC as a measure of negative or adverse experiences. The test–retest reliability of the LEC has been shown to be high (Brand & Johnson, 1982).

2.5 | Characterizing the sample

Table 1 shows that the primary caregiver's education in years for this sample is roughly equivalent to a 4-year college degree, with a wide range from elementary to postgraduate level completion. The mean sample income-to-needs ratio is 3.8, where an income-to-needs ratio of 1 is below the federal poverty line. The range of income-to-needs ratio includes families at or below the federal poverty line ($N = 17$) as well as families ranging well into the upper quadrants of wealth (e.g., income-to-needs ratio = 16.3). Finally, we have a wide range of scores on the HOME-SF and also have a wide range of scores on the reported number of negative life events on the LEC.

2.6 | Analysis plan

We first present results of the WM tasks. Second, we use confirmatory factor analyses to test our generated HOME-SF subscales (Tables 2 and 3). Third, we establish the relation among the LEC, HOME-SF subscales, and SES measures in our sample (Tables 5 and 6). Finally, we use mediation analyses (Hayes, 2009, 2013) to examine the relation of the HOME-SF subscales, LEC, and SES measures of parent occupation, education, and income with task performance (Tables 7 and 8). Figure 2 reflects that our path models specifically examined the subscales which were significant predictors of WM as mediators.

3 | RESULTS

3.1 | WM task results

Figure 3 illustrates both accuracy and RT data on the WM tasks. Accuracy statistically mirrored RT results and for brevity was not included in full in task results, except where noted on the Dimension Task. We calculated RTs in millisecond per child and block, excluding responses to the first trial of each experimental block, incorrect trials, and trials with latencies faster than 200 ms or slower than the outlier criterion determined on the basis of individual RT distributions. Baseline RTs decreased with Age, $r(114) = -0.391$, $p < 0.001$. Thus, Response Task Block 1 baseline RTs, where children simply pressed the same button regardless of stimulus, were entered as a covariate in the analyses of data from Feature and Dimension task. For the Response task, we applied a square root transformation to each participant's mean response latencies per task in order to increase the homogeneity of variance.

Data from Response, Feature, and Dimension tasks were separately subjected to GLMs to examine the cost of Block, going from Block 1 to Block 2 to Block 4 across Age (entered as a continuous variable). Recall that the task logic is that going from Block 1 to Block 2 represents an increase in updating a higher rule order into WM (WM updating) as well as increasing the number of alternatives maintained for action (from 1 to 2), whereas going from Block 2 to Block 4 increases only the demand on maintenance from 2 to 4 items (WM maintenance) at the same rule order. Significant interactions were examined further using planned paired comparisons, including pairwise comparisons by Age specifically regarding performance differences on Block 1 versus Block 2 (WM updating/maintenance increases) and Block 2 versus Block 4 (WM maintenance only). Bonferroni-corrected alpha was set to $p = 0.025$ for these tests.

On the Response task, we found a main effect of Block [$F(2, 224) = 84.19$, $p < 0.001$, $\eta_p^2 = 0.43$], a main effect of Age [$F(1, 112) = 105.62$, $p < 0.001$, $\eta_p^2 = 0.49$], and an Age by Block interaction [$F(2, 224) = 13.36$, $p < 0.001$, $\eta_p^2 = 0.11$]. Planned comparisons showed that the main effect of Block was driven by slower RTs for both WM updating (B1 vs. B2) [$t(113) = -22.82$, $p < 0.001$, as well as for WM maintenance increases (B2 vs. B4) [$t(113) = -7.80$, $p < 0.001$. However, the Age × Block interaction was driven only by better performance (faster RTs) with Age on the WM updating manipulation, as shown by a significant difference in the B1 by B2 comparison [$F(1, 112) = 13.56$, $p < 0.001$, $\eta_p^2 = 0.11$] and not the B2 by B4 comparison [$F(1, 112) = 1.60$), $p = 0.21$, $\eta_p^2 = 0.01$].

We found the same pattern with respect to Age on the Feature task, where there was a main effect of Age [$F(1, 110) = 85.56$, $p < 0.001$, $\eta_p^2 = 0.44$], Block [$F(2, 220) = 25.67$, $p < 0.001$, $\eta_p^2 = 0.20$], and an Age by Block interaction [$F(2, 220) = 9.37$, $p < 0.001$, $\eta_p^2 = 0.08$]. Paired comparisons showed statistically slower RTs as a function of the B1 versus B2 WM updating comparison [$t(114) = -17.85$, $p < 0.001$] and also the B2 versus B4 increase in WM maintenance [$t(114) = -3.66$, $p < 0.001$]. Again, Age interacted only with the B1 by B2 WM updating comparison [$F(1, 110) = 7.15$, $p = 0.009$, $\eta_p^2 = 0.06$], with costs decreasing as a function of Age. There was no Age by Block interaction for the B2 versus B4 WM maintenance manipulation, [$F(1, 110) = 3.72$, $p = 0.06$, $\eta_p^2 = 0.03$].

Finally, the Dimension task analysis yielded a main effect of Block [$F(2, 198) = 10.21$, $p < 0.001$, $\eta_p^2 = 0.09$] and a main effect of Age [$F(1, 99) = 26.97$, $p < 0.001$, $\eta_p^2 = 0.21$]. The main effect of Block was again driven by the B1 by B2 WM updating manipulation [$t(122) = -18.43$, $p < 0.001$], as well as the B2 versus B4 WM maintenance manipulation [$t(122) = -4.27$, $p < 0.001$]. However,

TABLE 3 Estimated factor–factor correlations for HOME-SF model

	Cognitive enrichment	Routine	Parental closeness	Restrictive parenting	Parental monitoring
Cognitive enrichment					
Routine	0.38				
Parental closeness	0.49	0.04			
Restrictive parenting	−0.15	0.18	0.07		
Parental monitoring	0.44	0.07	0.24	−0.05	
Supportive parenting	0.21	0.11	0.11	−0.21	0.10

Note. HOME-SF, Home Observation for Measurement of the Environment-Short Form.

we did not observe the expected Age by Block effect on RTs seen in the Response and Feature tasks above [$F(2, 198) = 1.63$, $p = 0.20$, $\eta_p^2 = 0.02$] and previously demonstrated in Unger et al. (2016). Unger et al. (2016) tested the interaction on RTs from three categorical age groups (children, adolescents, and adults). It is possible that the difficulty of the Dimension task resulted in very slow RTs for children and adolescents alike (Figure 3) and did not allow the Age by Block interaction to emerge here. Thus, we examined accuracy (percent correct responses) on the Dimension Task (Figure 3). Dimension task accuracy data showed main effects of Block [$F(2, 198) = 4.14$, $p = 0.02$, $\eta_p^2 = 0.04$], Age [$F(1, 99) = 24.91$, $p < 0.001$, $\eta_p^2 = 0.20$] and the expected Block by Age interaction [$F(2, 198) = 3.54$, $p = 0.03$, $\eta_p^2 = 0.04$]. Planned comparisons showed only an interaction with Age for the B1 versus B2 contrast [$F(1, 99) = 4.20$, $p = 0.04$, $\eta_p^2 = 0.04$], with higher accuracy costs in WM updating second-order relative to first-order rules. There was no Age by Block interaction for the B2 versus B4 WM maintenance manipulation, [$F(1, 99) = 0.44$, $p = 0.51$, $\eta_p^2 = 0.00$]. Taken together, the behavioral data show that developmental change in rule-guided action is driven by the cost of updating higher order rules into WM (WM updating, B1 vs. B2 contrast), over and above the cost of increasing the number of competing alternatives maintained for action at any single rule order (WM maintenance).

3.2 | Generation and confirmatory factor analyses on HOME-SF subscales

Subscales were chosen based on what were considered to be different forms of enrichment in the child's environment: cognitive enrichment (Cognitive Enrichment subscale), emotional enrichment (measured by subscales of Parental Closeness and Supportive Parenting), and the degree to which there was a structured environment in the home (measured by subscales of Routine and Parental Monitoring). We also included one measure designed to reflect restrictive or punitive parenting (Restrictive Parenting). Of these measures, we hypothesized only Cognitive Enrichment would be associated with our primary rule-guided behavior task measures.

We performed a CFA in Mplus 7.2 of the custom 6-subscale structure of the HOME-SF, to determine whether they measure coherent latent constructs. The factor structure is displayed in Tables 2 and 3, which present the individual items' factor loadings (Table 2) and factor–factor correlations (Table 3). Only items which had very low factor loadings (below 0.2) on any given factor were dropped from the analysis. Fit indices of the final model supported the proposed structure of items (RMSEA = 0.08, 95% C.I. (0.07, 0.08); $\chi^2 = 917$, $p < 0.001$). Subscales generally show adequate to good internal consistency in this sample (Cronbach's alphas between 0.67 and 0.88).

3.2.1 | Cognitive Enrichment subscale

The Cognitive Enrichment subscale of the HOME-SF consists of nine items about whether there is material stimulation in the child's home (e.g., the number of books and the presence of a musical instrument) and whether the child is encouraged to take on cognitively stimulating activities (e.g., reading and keeping regular hobbies). Questions were either ordinal or dichotomous, and responses were standardized before being summed into a scale. The Cronbach's alpha for this scale is 0.67.

3.2.2 | Routine subscale

The Routine subscale of the HOME-SF consists of five items which describe whether a child is regularly asked to do certain tasks (e.g., make his/her own bed and room). Responses were on a 5-point Likert scale ranging from 1 (*never*) to 5 (*always*). Responses were summed into a scale with a Cronbach's alpha of 0.88.

3.2.3 | Supportive Parenting subscale

This subscale of the HOME-SF is based on three items that ask how often the parent has shown different types of affection to the child

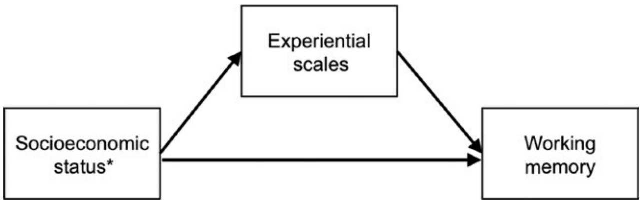

FIGURE 2 Illustrates path model. We used separate models for each measure of socioeconomic status (household income, income-to-needs ratio, parents' occupational level, and parents' years of education) as well as for the outcomes of working memory (WM) tasks. Mediators and WM task data were selected based on hypothesized effects and significance in previous models

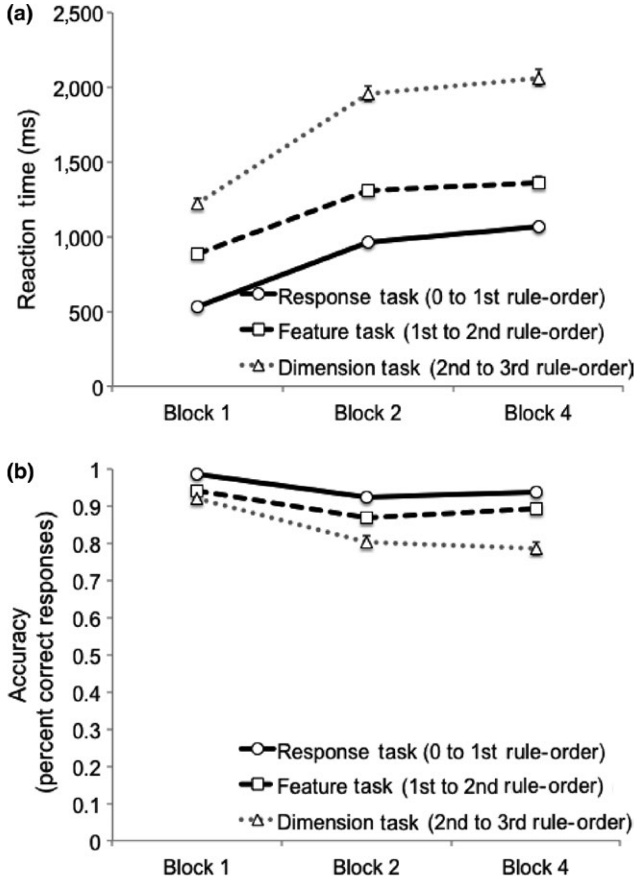

FIGURE 3 Response, Feature, and Dimension task performance for (a) RT (ms) and (b) accuracy (percent correct responses)

in the past week (praise the child, praise about the child to another adult, and physical affection). Responses were open-ended and standardized before being summed into a scale. The Cronbach's alpha for this scale is 0.70.

3.2.4 | Closeness to Parent subscale

This subscale measures the child's relationship with his/her parents through five items. There is one item about the presence of two parental caregivers, two items about how close the child is to their parents, on a 4-point Likert scale from 1 (*extremely close*) to 4 (*not close at all*), and two items about how often the child spends time with his/her parents on a 6-point Likert scale from 1 (*once a day or more*) to 6 (*never*). Items were standardized before being summed into a scale. The Cronbach's alpha for this scale is 0.68.

3.2.5 | Restrictive Parenting subscale

This subscale is based on nine items related to parents' use of punitive parenting. These included five dichotomous variables about hypothetical responses to a temper tantrum (e.g., taking away TV or taking away allowance), two items on a 5-point Likert scale from 1 (*very likely*) to 5 (*not at all likely*) in response to bringing home grades lower than expected (i.e., lecture the child and punish the child), and two items about how often the child was grounded or had privileges removed in the past week. Items were standardized before being summed into a scale, with a Cronbach's alpha of 0.72.

3.2.6 | Parental Monitoring subscale

This scale is comprised of three items that ask what actions a parent would take if the child brought home lower than expected grades: "contact the teacher or principal," "keep a closer eye on child's activities," and "spend more time helping child with school work." Item responses were on a 5-point Likert scale ranging from 1 (*very likely*) to 5 (*not at all likely*). The Cronbach's alpha for this scale is 0.67.

For comparison, in this sample, the standard Cognitive Stimulation and Emotional Support measures from the HOME-SF have Cronbach's alphas of 0.68 and 0.61, respectively. Confirmatory factor analysis of the standard two-scale model showed fit statistics which are similar to our proposed 6-factor model (RMSEA = 0.09, 95% C.I. (0.08, 0.11); $\chi^2 = 356$, $p < 0.001$).

As noted, the LEC measures the number of negative life events. Table 4 shows the frequency of participants exposed to specific negative life events measured in the LEC.

3.3 | Relationship between experiential measures and SES

Next, we statistically defined which of the experiential measures described above related to SES in our sample. Table 5 shows the correlation among our three SES measures, the HOME-SF subscales, and LEC data. The HOME-SF Cognitive Enrichment subscale is correlated with SES variables: parent education, occupation, and income, as are various parenting measures that were designed to elucidate emotional enrichment and parenting style in the home. As indicated by Table 5, there is no correlation between SES and number of negative life events as measured by the LEC.

We next used separate regression models to assess the predictive relations between the SES, HOME-SF subscales, and LEC data. Analyses were conducted in Stata 14. Table 6 presents results of our measures of SES predicting the HOME-SF subscales and LEC. In our sample, parents' occupation, higher mother's (parent 1) education, higher income, and higher income-to-needs ratio are significantly associated with higher values on the Cognitive Enrichment subscale. For example, a 1-level increase on the parental occupation scale is associated with more than a 0.3 standard deviation increase in Cognitive Enrichment in this sample. Simultaneously, mother's education and family income variables are associated with lower levels of Parental Closeness. Mother's education and family income are also associated with lower levels of Restrictive Parenting, and mother's occupation is associated with higher levels of Parental Monitoring. None of our SES measures statistically related to differences in adverse or negative experiences as indicated by the LEC. Thus, in our sample, SES reflects Cognitive Enrichment, as well as differences in caregiving style.

TABLE 4 Frequency of LEC negative events in whole sample

Event	Frequency (# participants exposed)
Serious illness or injury of family member	62
Increased number of arguments between parents	43
Trouble with brother or sister	40
Death of a family member	36
Trouble with classmates	36
Change in parents' financial status	32
Trouble with teacher	28
Changing to a new school	21
Increased absence of parent from home	20
Failing a grade	20
Increase in number of arguments with parents	20
Major personal illness or injury	18
Mother or father lost job	17
Failing to make an athletic team	14
Making failing grades on report card	14
Moving to a new home	10
Serious illness or injury of close friend	10
Losing a close friend	10
Breaking up with boyfriend/girlfriend	10
Brother or sister leaving home	8
Parents divorced	6
Parent getting into trouble with law	6
New stepmother or stepfather	6
Getting into trouble with police	6
Death of a close friend	6
Parents separated	4
Being suspended from school	4
Parent going to jail	2
Male: girlfriend getting pregnant	2
Losing a job	2
Male: girlfriend having abortion	2
Getting put in jail	2
Female: getting pregnant	0
Female: having abortion	0

Note. LEC, Life Events Checklist.

3.4 | Testing the direct effects of SES on WM updating and WM maintenance

We first take the intermediate statistical step of establishing which subscales predicted task performance, but without consideration for SES. We used separate models to assess the relations between the SES, HOME-SF subscales, and LEC data and task measures (accuracy and RT costs separately). All models including measures of HOME-SF subscales/LEC or task measures also controlled for age-related differences in performance. Missing data were generally small (under 10%) except for the variables of household income (31%) as well as primary and secondary parent occupation (37% and 19%, respectively). We used maximum likelihood with missing values to retain observations with missing values. This approach is considered to be more efficient and less sensitive to decision making than multiple imputation (Allison, 2012). Note that models excluding missing values (not shown) produced substantively similar results. All model estimates are based on 5,000 bootstrap replicates. Only variables that were initially hypothesized to be associated with task-dependent variables, as well as those that were reliable at each analytic step, were examined further in order to avoid false positives findings resulting from multiple comparisons. Analyses were conducted in Stata 14.

Table 7a presents the results of separate regressions examining the effects of the HOME-SF subscales and the LEC number of negative events on WM updating and WM maintenance RT performance. WM updating costs were calculated by subtracting B2–B1 response, and WM maintenance costs were calculated by subtracting B4–B2 responses separately for each task.

The Feature task provided the clearest results. Of the subscales developed from a CFA of the HOME-SF, only Cognitive Enrichment was significantly associated with both RT and accuracy difference scores (Tables 7a and 8a respectively, see also Figure 4). There was a positive association of HOME-SF Cognitive Enrichment subscale with RT and accuracy in WM updating. Higher levels of Cognitive Enrichment are associated with better accuracy (higher values for Block 2 minus 1 reflect smaller cost of increase in rule order) and higher WM updating costs in RTs. The Response task showed the same pattern for RTs (Table 7a) and accuracy (Table 8a). However, the accuracy data were not reliable, possibly because accuracies were quite high in this age group on the Response task.

Moreover, higher Cognitive Enrichment and more negative life events (LEC) were associated with general effects on WM accuracy (Table 8a). On the Response task, the HOME-SF Routine subscale predicted better WM updating and WM maintenance performance. On the Feature Task, the LEC predicted poorer WM updating and WM maintenance performance. Note that the sign of the WM maintenance coefficient is determined by the subtraction of Block 4 minus Block 2. To the extent that some children had similar or higher accuracy on Block 2 (see Figure 3), a negative coefficient reflects smaller costs with an increase in the predictor. We found no effects again on the Dimension task. Note that we verified that all measures had independent effects on task performance by examining them in models simultaneously with other HOME-SF variables.

These data indicate unsurprisingly that both positive and negative life experiences impact cognitive control at the level of WM updating and WM maintenance (Conger & Donnellan, 2007; Johnson et al., 2016; Ursache & Noble, 2016). We have yet to statistically establish any evidence that these relations are relevant to

TABLE 5 Correlations of independent measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Parent education in years												
(2) Parental occupation level[a]	0.78*											
(3) Household income in dollars	0.57*	0.41*										
(4) Income-to-needs ratio	0.57*	0.37*	0.97*									
(5) HOME-SF cognitive enrichment	0.26*	0.38*	0.43*	0.38*								
(6) HOME-SF routine	−0.18*	−0.08	0.08	0.04	0.23*							
(7) HOME-SF parental closeness	0.21*	0.10	0.24*	0.22*	0.33*	0.01						
(8) HOME-SF restrictive parenting	−0.31*	−0.11	−0.22*	−0.30*	−0.06	0.17	0.01					
(9) HOME-SF supportive parenting	0.06	−0.03	0.05	0.05	0.20*	0.03	0.14	−0.16				
(10) HOME-SF parental monitoring	0.01	0.18	0.08	0.12	0.25*	0.06	0.12	−0.04	0.16			
(11) LEC # negative life events	0.01	−0.08	0.02	0.04	−0.18*	−0.07	0.18*	0.04	−0.06	0.08		
(12) Age	−0.03	−0.07	0.08	0.08	−0.22*	0.09	−0.40*	−0.05	−0.21*	−0.08	0.12	
(13) Woodcock–Johnson GIA	0.38*	0.33*	0.35*	0.26*	0.27*	0.11	0.07	−0.16	0.03	−0.03	−0.19*	0.03

Notes. GIA: General Intelligence Ability; HOME-SF, Home Observation for Measurement of the Environment-Short Form; LEC, Life Events Checklist.
[a] Parent occupational level coded using O*Net ratings available through the US Department of Labor on a scale of 1–5.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

SES. That is, these data do not show that SES is working through any of these experiential variables to impact cognitive control and WM. In the next critical step, we systematically test whether SES is working indirectly through any of the effects observed in Tables 7a and 8a.

3.5 | Testing indirect effects of SES on WM through HOME-SF and LEC subscales

In this final step, we examined whether any of the observed effects on WM performance are linked to SES. As noted, only variables that were reliable at the previous analytic step were examined further to avoid false-positive errors. In particular, we had predicted that SES exhibits an indirect influence on WM updating through the Cognitive Enrichment subscale. Table 7b shows the results of the separate path analyses for each of the SES measures of interest predicting WM updating and maintenance RT costs, with the Cognitive Enrichment subscale as the mediator. The results show that our various measures of SES do not exhibit a statistically significant "total effect" on our WM outcomes. However, particularly through income variables, SES is positively associated with higher WM updating costs, indirectly through its influence on the Cognitive Enrichment subscale for both the Response and Feature tasks. Table 8b shows the results of the separate path analyses for each of the SES measures of interest predicting WM updating and maintenance accuracy costs, with the Cognitive Enrichment subscale as the mediator. SES variables of household income, income-to-needs, and caregiver education and occupation exhibit indirect effects through the Cognitive Enrichment subscale. Higher Cognitive Enrichment shows better performance as indicated by smaller accuracy costs for WM updating. Finally, Table 8c,d shows that the observed effects of LEC and Routine on task performance were unrelated to SES in our sample. Taken together, these data indicate that SES, through Cognitive Enrichment, is driving a more successful strategy for higher accuracy and slower RTs in WM updating.

In order to explore this trade-off, we adapted the rate residual score method of Hughes, Linck, Bowles, Koeth and Bunting (2014), which incorporates both RT and accuracy data into a single rate residual score. This allows assessment of how an individual differs from the group in speed and accuracy, simultaneously, as

TABLE 6 Regression models of socioeconomic status predicting HOME-SF and LEC subscales

	Cognitive enrichment	Routine	Parental closeness	Restrictive parenting	Parental monitoring	Supportive parenting	LEC (# Negative events)
Household income in dollars	0.01^{***}	0.00	0.00^{*}	-0.00^{***}	0.00	0.00	0.00
Income-to-needs ratio	0.19^{***}	0.02	0.10	-0.13^{***}	0.05	0.04	0.09
Parent 1 Education in years	0.13^{**}	−0.08	0.07^{*}	-0.14^{***}	0.01	0.05	−0.01
Parent 2 Education in years	0.07	−0.05	−0.08	-0.08^{**}	0.00	0.00	0.03
Parent 1 Occupation level	0.34^{*}	−0.22	−0.03	−0.14	0.29^{*}	0.05	0.32
Parent 2 Occupation level	0.31^{*}	−0.05	0.07	−0.15	0.03	−0.09	−0.59

Notes. HOME-SF, Home Observation for Measurement of the Environment-Short Form; LEC, Life Events Checklist.
Cells represent beta coefficients predicting task reaction time in regression models with 5,000 bootstrap replications, controlling for age of child. Missing data accounted for with maximum-likelihood maximum variation.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

TABLE 7 (a) Direct effects of experiential scales on task RT (ms) performance. (b) Magnitude of indirect effect of socioeconomic variables on WM updating cost reaction time through cognitive enrichment subscale of HOME-SF

	WM response task		WM feature task		WM dimension task	
(a)	Updating	Maintenance	Updating	Maintenance	Updating	Maintenance
HOME-SF cognitive enrichment	33.80^{*}	22.29	6.14^{***}	1.25	36.84	1.10
HOME-SF routine	−14.76	19.39	4.45	−5.99	35.32	2.72
HOME-SF parental closeness	−6.40	16.98	12.38	16.40	−49.45	−31.57
HOME-SF restrictive parenting	−2.87	3.66	26.99	−19.17	−39.56	−11.14
HOME-SF parental monitoring	26.37	−7.16	4.72	−4.84	−7.61	−1.87
HOME-SF supportive parenting	−16.85	5.94	−3.63	1.73	−31.42	27.24
LEC # Negative life events	−1.26	1.08	−14.65	3.26	−1.13	2.35

	WM response task, updating			WM feature task, updating		
(b)	Total	Direct	Indirect	Total	Direct	Indirect
Household income in dollars	0.04	−0.42	0.45^{**}	0.31	−0.37	0.67^{**}
Income-to-needs ratio	0.29	−1.72	11.02	8.23	−7.82	16.06**
Parent 1 Education in years	2.29	−1.67	3.96	−4.48	−12.88	8.40^{*}
Parent 2 Education in years	−2.54	−4.85	2.31	3.56	−0.55	4.11
Parent 1 Occupation level	15.07	3.18	11.89	1.59	−7.17	17.76
Parent 2 Occupation level	−3.82	−9.73	5.91	23.38	15.32	8.07

Notes. HOME-SF, Home Observation for Measurement of the Environment-Short Form; LEC, Life Events Checklist; WM, working memory.
Cells represent beta coefficients predicting task reaction time in regression models with 5,000 bootstrap replications, controlling for age of child. Missing data accounted for with maximum-likelihood maximum variation.
"Updating" represents cost of updating higher order rules into WM and "Maintenance" represents cost of increasing alternatives for action at the same level. "Updating" is calculated as difference between Level 1 and Level 2 (Block 2 − Block 1). "Maintenance" is calculated as difference between Level 2 and Level 4 (Block 4 − Block 2).
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

a function of Age and Cognitive Enrichment score. Rate residual scores were based on the rate of correct responding per second. Rate residual scores were computed separately for the Response, Feature, and Dimension tasks. The rate of correct responding was calculated by dividing the average number of correct responses per trial (e.g., Response task, Block 1) by the average time taken across all responses in that trial. Using these rates of correct responding, rate residual scores were calculated by regressing the

TABLE 8 (a) Direct effects of experiential scales on task accuracy (percent correct responses) performance; Magnitude of indirect effect of socioeconomic variables on WM updating and maintenance cost accuracy through (b) Cognitive Enrichment subscale of HOME-SF, (c) LEC Negative Life Events Scale, (d) Routine subscale of HOME-SF

	WM response task		WM feature task	
(a)	Updating	Maintenance	Updating	Maintenance
HOME-SF cognitive enrichment	0.008	−0.004	0.031**	−0.030***
HOME-SF routine	0.016*	−0.013**	0.012	−0.015
HOME-SF parental closeness	−0.003	0.011	0.020	−0.012
HOME-SF restrictive parenting	0.002	−0.005	0.007	−0.002
HOME-SF parental monitoring	0.004	−0.005	−0.004	−0.004
HOME-SF supportive parenting	0.002	−0.001	−0.002	−0.012
LEC # negative life events	−0.003	0.002	−0.006*	0.007**

	WM feature task, updating			WM feature task, maintenance		
(b)	Total	Direct	Indirect	Total	Direct	Indirect
Household income in dollars	0.000	0.000	0.000	0.000	0.000	−0.000**
Income-to-needs ratio	−0.001	−0.008	0.007*	−0.002	0.005	−0.006**
Parent 1 Education in years	0.002	−0.002	0.004*	0.003	0.007	−0.004*
Parent 2 Education in years	0.004	0.002	0.002	0.002	0.004	−0.002
Parent 1 Occupation level	0.004	−0.006	0.010	0.009	0.019	−0.010*
Parent 2 Occupation level	0.015	0.005	0.010*	0.002	0.013	−0.011*

	WM feature task, updating			WM feature task, maintenance		
(c)	Total	Direct	Indirect	Total	Direct	Indirect
Household income in dollars	0.000	0.000	0.000	0.000	0.000	0.000
Income-to-needs ratio	0.000	0.000	0.000	−0.001	−0.001	0.001
Parent 1 Education in years	0.001	0.001	0.000	0.003	0.003	0.000
Parent 2 Education in years	0.004	0.004	0.000	0.002	0.002	0.000
Parent 1 Occupation level	0.002	0.004	−0.002	0.012	0.010	0.002
Parent 2 Occupation level	0.014	0.010	0.004	0.000	0.005	−0.005

	Response task, WM updating			Response task, WM maintenance		
(d)	Total	Direct	Indirect	Total	Direct	Indirect
Household income dollars	0.000	0.000	0.000	0.000	0.000	0.000
Income-to-needs	0.004	0.004	0.000	−0.002	−0.002	0.000
Parent 1 Years of education	0.000	0.002	−0.001	0.000	−0.001	0.001
Parent 2 Years of education	0.000	0.001	−0.001	0.003	0.003	0.001
Parent 1 Occupation	0.001	0.005	−0.003	0.001	−0.002	0.003
Parent 2 Occupation	−0.013	−0.012	−0.001	0.008	0.007	0.001

Cells represent beta coefficients predicting task accuracy in regression models with 5,000 bootstrap replications, controlling for age of child. Missing data accounted for with maximum-likelihood maximum variation.

"Updating" represents cost of updating higher order rules into WM and "Maintenance" represents cost of increasing alternatives for action at the same level. "Updating" is calculated as difference between Level 1 and Level 2 (Block 2 − Block 1). "Maintenance" is calculated as difference between Level 2 and Level 4 (Block 4 − Block 2).

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

higher level condition on the lower level condition: For WM updating, the score was calculated using the residualized difference between the rates of correct responses per second for Block 2 and Block 1; for WM maintenance, the score was calculated using the residualized difference between the rates of correct responses per second for Block 4 and Block 2. Using this measure, a larger cost is indicated by more negative residuals. Predictive models used rate residual scores as the dependent variable and Cognitive Enrichment, a binary Age variable (children ages 12 years and older coded as "1") and an interaction with Age and

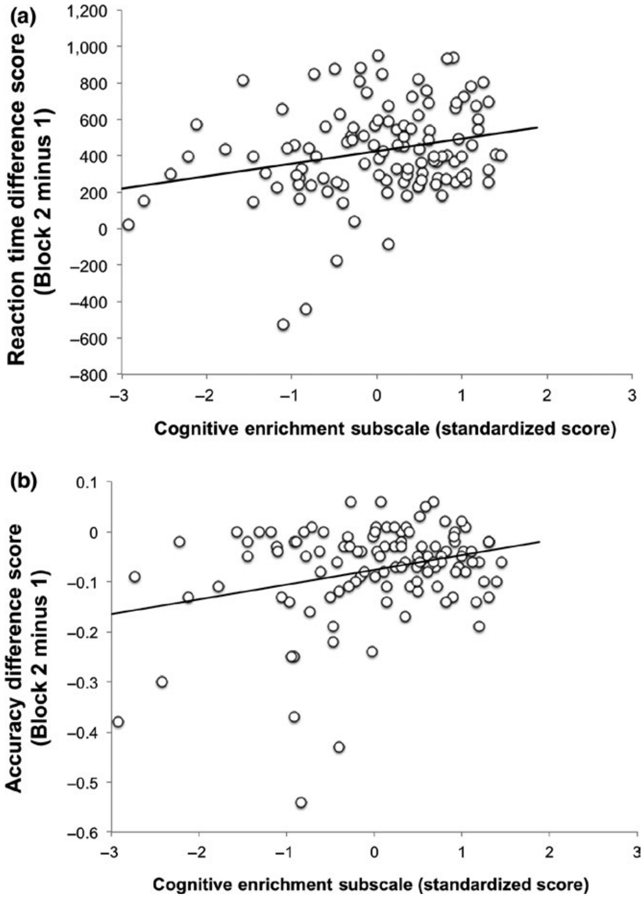

FIGURE 4 Simple correlations to illustrate the Feature task working memory (WM) updating performance for (a) accuracy and (b) reaction time costs (Block 2 − Block 1) as a function of Cognitive Enrichment subscale scores

Cognitive Enrichment as the independent variables. Age had a strong, positive association with WM updating on the Response task ($\beta = 0.289$, $p < 0.001$), indicating a smaller cost for older participants. In addition, for the WM updating on the Response task, we find that there is a significant interaction between Cognitive Enrichment and Age ($\beta = -0.085$, $p = 0.03$), such that Cognitive Enrichment has increased magnitude of cost for those older than 12 years of age. Put another way, RT slowing in the service of accuracy occurs as a function of Cognitive Enrichment, and this effect is less pronounced in younger children on the Response Task when demands are placed on WM updating. The trade-off in rate residual score is otherwise not significantly different across Age in the more challenging Feature task.

Finally, there was also an effect of Cognitive Enrichment on WM maintenance accuracy (Table 8a,b, Figure 5). The negative sign of this WM maintenance coefficient is driven by the finding that more Cognitive Enrichment was associated with better performance on Block 2 relative to Block 4 in some children. This means that anyone with a negative value for the Block 4 minus 2 WM maintenance difference score is showing no WM maintenance cost. For the remainder of children (with difference scores above 0), higher Cognitive Enrichment is associated with better performance on WM maintenance. To ensure this interpretation of our data is accurate, we ran a sensitivity analysis examining whether the effect of Cognitive Enrichment depended on the direction of change between these two blocks. For those whose accuracy decreased as expected (i.e., was worse for Block 4 than Block 2), the effect of Cognitive Enrichment was reliable and remained in the same direction as the main effect ($\beta = -0.02$, $\alpha = 0.005$, CI [−0.03, −0.01]). For those whose accuracy increased (i.e., improved for level 4 relative to 2), the effect was also reliable and in the same direction ($\beta = -0.03$, $\alpha < 0.001$, CI [−0.049, −0.02]).

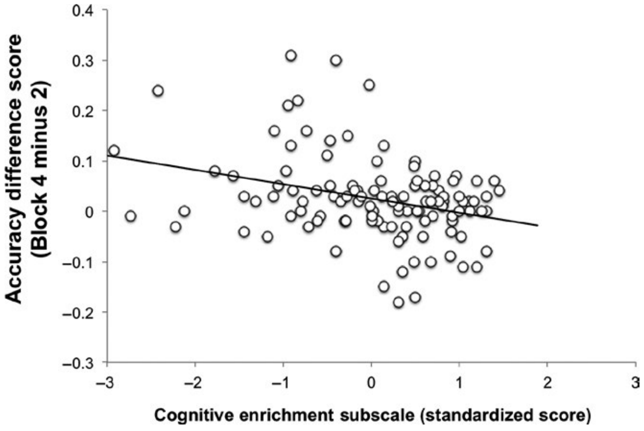

FIGURE 5 Simple correlations to illustrate the Feature task accuracy for working memory (WM) maintenance (Block 4 − Block 2) as a function of Cognitive Enrichment subscale scores

3.6 | Control analyses: LEC impacts IQ

Socioeconomic status has been shown to impact general IQ (Nisbett et al., 2012). Table 9 shows that there were effects of HOME-SF and LEC subscales on GIA (our IQ measure) but that our task performance was unrelated to GIA. This analysis shows that the LEC number of negative life events measure has the expected effects on general IQ in our sample. Moreover, the HOME-SF subscales were not only sensitive to task performance but also to GIA. However, our effects of Cognitive Enrichment on task performance could not have been driven by more general effects of Cognitive Enrichment on intelligence, as GIA was unrelated to WM task performance. Table 9 shows that GIA scores are unrelated to the cost of increasing WM maintenance and updating, which is the only specific measure of the WM demands added by higher order rules. Therefore, our effects cannot be attributable to a general effect of IQ.

4 | DISCUSSION

Socioeconomic status impacts brain and cognitive development not only for children living in poverty, but also across the entire SES

TABLE 9 Control analyses showing effects of general intelligence

	WJ GIA
LEC, # negative events	−0.89*
HOME-SF cognitive enrichment	4.20**
HOME-SF routine	1.40
HOME-SF parental closeness	−2.23*
HOME-SF restrictive parenting	−0.36
HOME-SF parental monitoring	0.62
HOME-SF supportive parenting	1.44
Response task—Updating cost	0.95
Response task—Maintenance cost	0.80
Feature task—Updating cost	2.00
Feature task—Maintenance cost	−0.61
Dimension task—Updating cost	4.16
Dimension task—Maintenance cost	1.57

Notes. GIA: General Intelligence Ability; HOME-SF: Home Observation for Measurement of the Environment-Short Form; LEC: Life Events Checklist.
Cells represent beta coefficients predicting task reaction time in regression models with 5,000 bootstrap replications, controlling for age of child. Missing data accounted for with maximum-likelihood maximum variation.
Woodcock–Johnson GIA values are standardized scores.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

spectrum. An important goal of developmental research is to understand the role SES plays in shaping health and achievement outcomes. This understanding is key to informing policy that addresses the mechanisms underlying wealth and education inequality, as well as intergenerational mobility. We systematically investigated the influences for which SES is a proxy, in a typical sample of children, on the development of rule-guided behavior. This is a cognitive control skill shown to involve the PFC and to engage WM updating and WM maintenance mechanisms. We based our predictions on computational and behavioral data that indicate that variability of experiences in which to implement rule-guided action is key to the efficiency of this skill (Rougier et al., 2005). Overall, our data are consistent with our prediction that SES acts as a proxy for enrichment opportunities that shape the mechanisms underlying rule-guided behavior.

Table 1 shows that our sample is made up of children from a wide range of SES, but with relatively few children reporting a high number of negative or traumatic experiences as measured by the LEC (see also Table 4). Table 5 shows that LEC was unrelated to any of the SES measures. This is a strength of this study. There is a wide distribution of wealth and education in America that impacts child development in important ways that are unrelated to extreme adversity. Our specific question was how SES, not stress, is shaping cognitive control. Table 5 indicates that variation in SES does not, in our sample, mean a larger number of adverse or traumatic experiences. This finding is consistent with the literature discussed in the introduction showing that SES measures do not regularly correlate with fluctuations in cortisol levels. Other data have repeatedly shown that some stressful life events are more common in *high* SES homes. Extensive research from Luthar and colleagues has demonstrated that high SES homes and schools impose stressors for unrealistic achievement that result in high rates of internalizing disorders and substance abuse by early adolescence (Ansary, McMahon, & Luthar, 2017; Ciciolla, Curlee, Karageorge, & Luthar, 2017; Coren & Luthar, 2014; Luthar, Small, & Ciciolla, 2018). In our sample, children who did experience negative or traumatic experiences as measured by the LEC were scattered across the SES continuum.

Table 6 shows that SES predicted only the HOME-SF Cognitive Enrichment, Parental Closeness, and Restrictive Parenting subscales in our sample. The Cognitive Enrichment subscale was designed to index material enrichment items and learning opportunities in a child's environment. Higher SES was associated with higher Cognitive Enrichment and also Parental Closeness. The Parental Closeness subscale was designed to index the child's relationship quality with his/her parents. Restrictive Parenting, in contrast, was negatively associated with SES. Restrictive Parenting measured punishment severity given child behavior. This analytic step, whereby we measure and identify the experiences for which SES is a proxy, allows us an understanding of the experiences that SES is indexing in our sample.

Relevant to cognitive control, we found that higher levels of Cognitive Enrichment are associated with higher accuracy and a greater RT cost to updating rules into WM, most strongly in the Feature task (first- to second-order rule increase). In the Response task, this effect is more pronounced in the older end of the age range, but it is otherwise uniform across Age in the Feature task. The Response task finding is consistent with the Amso et al. (2014) where we showed that SES effects on cognitive control emerged with age in the transition to adolescence on the same tasks. Specifically, Tables 7 and 8 show that SES has an indirect effect on WM updating performance through the Cognitive Enrichment subscale for both RT (Table 7b) and accuracy (Table 8b). These data suggest that more Cognitive Enrichment in the home environment is associated with engaging a strategy that sacrifices speed to maximize WM updating accuracy in the service of flexible rule-guided behavior. Higher Cognitive Enrichment in the home environment was also associated with better accuracy performance on WM maintenance in the Feature task.

Perhaps, our most important finding is that not all SES correlates in our sample impacted cognitive control performance, and not all experiential variables that impacted cognitive control performance were associated with SES. Tables 7 and 8 show both direct effects of experiential variables, followed by whether they are associated with SES. Table 8a shows that the number of reported negative life events had an impact on Feature Task accuracy performance. Table 8c shows that this was independent of SES. SES acted indirectly to impact cognitive control only through the Cognitive Enrichment subscale. In other words, LEC metrics are important for understanding the shaping of cognitive control, and cognitive development more broadly, *but they are orthogonal* *to an investigation of the impact of SES on cognitive control*. Similarly, Parental Closeness and Restrictive Parenting were associated with SES in our sample (Table 6) *but did not impact cognitive control task performance* (Tables 7 and 8). Put another way, in order to inform evidence-based policy designed to alleviate the impact of SES on cognitive control development, we must isolate SES as separate from the myriad other variables that impact cognitive control. These statistical distinctions are key to unraveling SES influence on cognitive development.

The goal of any investigation is to generalize to the population that a sample represents. These data were collected between 2012 and 2016. The only SES measure that allows us to interpret our results, with respect to a broad community of children with similar SES, is income. The US Census cites the median income for a family of 4 was between $68,000 and 73,000 (2015). On average, our sample median income, calculated across all family sizes, was higher than the national average (Table 1). This is not at all uncommon in studies of SES (Noble, Houston, et al., 2015; Piccolo et al., 2016). For example, two studies have used the Pediatric Imaging, Neurocognition, and Genetics Study to examine SES effects on structural brain development. This is a multisite structural neuroimaging study of over 1,000 participants aged 3–20 years. Family income ranges from $4,500 to $325,000, with a mean of $97,617 (*SD* = $76,719). Given who our sample is with respect to SES (income, education) and trauma and adversity, we cannot in good faith interpret our results in accord with deprivation (Sheridan et al., 2017; Sheridan & McLaughlin, 2016) in the relatively lower SES homes in the sample. The lower SES homes in our sample fall within the majority of American households. To call their experience deprivation would be to mischaracterize the normative experience. It is the higher SES children that are “out of typical range” for income. Consistently, SES acted through the Cognitive Enrichment subscale of the HOME-SF. This subscale indexed material stimulation in the child’s home (e.g., the number of books and the presence of a musical instrument) and whether the child is encouraged to engage in cognitively stimulating activities (e.g., reading and keeping regular hobbies). We interpret these data to mean that availability of material enrichment in the home is important for rule-guided behavior, and specifically WM, in childhood and adolescence across our wide income range. This finding is entirely consistent with the predictions generated from the Rougier et al. (2005) modeling data. Those data indicated that learning similar rule structures across variable tasks elicited better flexibility in novel contexts.

It is relevant that the strongest and clearest effects were for the Feature task. Recall that the three tasks engage the same cognitive control operations, but parametrically ranged in their demands on WM. The Feature task may have been “just right” for this age range, meaning that it was appropriate and sufficiently challenging for the full age range tested. Unlike the Response and Feature tasks (Amso et al., 2014), the Dimension task has never been considered with respect to SES. None of the SES or subscale measures predicted performance in our sample on the Dimension task. This may be partly due to the task being overly challenging for this sample age range (Figure 3). Lawson, Hook, et al. (2017) recently performed a meta-analysis of the literature on SES and executive functions. They found mixed results and only a medium effect size. Executive functions, or cognitive control, are a multifaceted construct that shows developmental change into adolescence. From a design perspective, it is critical to properly define the skill under investigation and to choose a task that is age appropriate. Design choices may need to consider both which task is chosen (rule use, WM load manipulations, set shifting) and also whether the parametric variant is appropriate for the age group. Parametric manipulations have long been effective design choices in neuroimaging experiments for the study of cognitive control and have been used to equate behavioral performance across age groups so that PFC activity can be directly compared. Our data, from three identical WM tasks of varying difficulty, suggest that parametric manipulations may additionally be an important consideration in the design of SES experiments.

The effects of SES on rule-guided behavior were initially reported in Amso et al. (2014) in an exploratory analysis. Both the current study and Amso et al. (2014) found WM updating performance optimization related to SES. However, this effect was expressed (either in speed or accuracy) differently across the samples. In particular, there was not a strategy of maximizing WM accuracy (and slowing of RTs) in Amso et al. (2014). Rather, Amso et al. (2014) found that individuals from higher SES homes had relatively faster RTs.

The reasons for these differences across samples are not entirely clear. Subtle differences in how an experimenter stresses speed or accuracy can influence response strategies. It is possible that the experimenters may have implicitly emphasized accuracy more than speed in the learning phase of the task. Moreover, the precision of the HOME-SF subscale analyses used here allowed us to better measure more fine-grained differences in accuracy performance than was possible in Amso et al. (2014), where demographic measurement was limited to a single crude SES composite measure, and thus lacked the precision in measurement offered here. Neither Amso et al. (2014) nor this study showed any effect of SES on WM maintenance RTs. However, the precision offered here may have allowed an effect of SES, through Cognitive Enrichment, to be measurable on Feature task WM maintenance accuracy. This effect was interesting in that some children showed no cost to maintenance increases (difference score below 0 in Figure 5) and indeed may have performed worse on Feature task Block 2 than Block 4. Recall that both required updating second-order rules into WM and Block 4 does so with an increased demand on WM maintenance load. One possible explanation has to do with the possibility that one can succeed on Block 4 using a flat rather than hierarchical structure. That is, regardless of how they were taught the task, children can opt to learn to map four separate box colors to four separate arrow directions in Block 4. This is not a strategy that can be used in Block 2. Thus, it may be that children with a negative difference score in Figure 3 were opting for a less effortful strategy in Block 4. Nonetheless, the follow-up analyses show that even in those with the positive difference scores, the effect of SES through Cognitive Enrichment predicted smaller costs.

We note here limitations of our study. First, we did not randomly assign children to SES groups. Any such investigation of SES influences on development is limited in its ability to draw causal inferences. Second, our data are not designed to offer a general theory of SES action on cognitive development. SES effects have been shown to impact memory and language as well as WM (e.g., Noble, McCandliss & Farah, 2007). The effect of SES on these other constructs may or not be uniquely through cognitive enrichment. A systematic approach, like the one used here, may offer clarity. Finally, it is important to note that the number of reported negative life events on the LEC was associated with General Intelligence score (Table 9), indicating that there was sufficient variability to detect expected effects of stressors on IQ (Nisbett et al., 2012). However, our measures of stress are limited. The LEC asks about recent experiences, and thus, we are not able to speak to the impact of adversity experienced earlier in life. We also did not examine cortisol levels, necessary for biological stress measurement (Blair et al., 2011; Evans & English, 2002; Lupien et al., 2000; Tarullo & Gunnar, 2006), limiting our ability to draw conclusions about SES, stress biology, and WM. Finally, GIA in our data was not related to WM performance. This was also true in a separate sample of children tested on the same tasks in Amso et al. (2014). The GIA score used in this paper is a general ability score, which has been argued to be distinct from fluid intelligence, and the latter has been found to be correlated with WM (Blair, 2006). However, the literature on this relation is still being debated. For example, some have provided evidence that high correlations between fluid intelligence and WM depend on which definition of WM as a construct is used (Ackerman, Beier & Boyle, 2005). Others have argued that the relationship may reflect speed of processing within individuals rather than WM proper (Conway, Cowan, Bunting, Therriault & Minkoff, 2002; Fry & Hale, 2000; Salthouse, 1996; Salthouse & Pink, 2008).

For policy, mechanistic precision offers opportunity for effective investment in programs that work on the specific problems children and families experience. Our data suggest that SES is supporting cognitive control development to the extent that children have various cognitively stimulating items and opportunities that allow them to practice rule-guided behavior. This is consistent with the literature on the types of policy-based programs that have been shown to support positive progress in narrowing the achievement gap (Amso & Lynn, 2017). For example, the Chicago Readiness School Project (Raver et al., 2011) focused on teaching children self-regulation in the classroom and in a variety of contexts. This program improved performance on a host of academic skills. Others have shown that involvement in various structured opportunities in the arts, play, skills development, martial arts, sports, etc. all support executive functions development (Diamond & Lee, 2011). This type of in-depth analysis into the experiences for which SES is a proxy may be a necessary step in determining how best to interpret SES effects in future investigations and to use that information to inform education and policy.

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CONFLICT OF INTEREST

We have no conflicts to disclose.

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