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Attitudes Toward Math Are Differentially Related to the Neural Basis of Multiplication Depending on Math Skill

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Abstract

Attitudes toward math (ATM) predict math achievement. Negative ATM are associated with avoidance of math content, while positive ATM are associated with exerting more effort on math tasks. Recent literature highlights the importance of considering interactions between ATM and math skill in examining relations to achievement. This study investigated, for the first time, the effects of the interaction between math skill and ATM on the neurocognitive basis of arithmetic processing. We examined the effect of this interaction using a single-digit multiplication task in 9- to 12-year-old children. Results showed that higher math skill was correlated with less activation in the left inferior frontal gyrus (IFG), and positive ATM were correlated with less activation in the left IFG. The relation between ATM and the neural basis of multiplication varied depending on math skill. Only among children with lower math skill, positive ATM were associated with greater activation of the left IFG. The results suggest that positive ATM in low-skill children might encourage them to more fully engage the neurocognitive systems underlying controlled effort and retrieval of multiplication facts. Our results highlight the importance of examining the role of both attitudinal and cognitive factors on the neural basis of arithmetic development.

Keywords

math attitudes, fMRI, arithmetic, mathematics, math skill, multiplication

Succeeding in mathematics predicts later well-being, satisfaction with life, health, wages, employment, and longevity (Reyna & Brainerd, 2007; Rivera-Batiz, 1992). Achievement in mathematics varies with a wide range of factors, such as students' skill, socioeconomic variables, parent and peer influences, and school-related variables (Singh, Granville, & Dika, 2002). Among those factors, attitudes toward math (ATM) strongly predict success and persistence in math (Singh et al., 2002). Attitudes are defined as "a learned predisposition or tendency on the part of an individual to respond positively or negatively to some object, situation, concept, or another person" (Aiken, 1970, p. 551). Although multiple definitions of ATM exist, one of the earliest and most commonly used one is by Neale, who described ATM as "an aggregated measure of a liking or disliking of mathematics, a tendency to engage in or avoid mathematical activities, a belief that one is good or bad at mathematics and a belief that mathematics is useful or useless" (Neale, 1969, p. 632). Here, ATM are described as consisting of two aspects: interest in math and self-perceived skill in math (Chen et al., 2018). Our goal is to examine how ATM and math skill interact in influencing the neural basis of single-digit arithmetic.

A meta-analysis of 113 studies, using Neale's definition of ATM, showed a small, but significant relationship between ATM and math achievement (overall mean effect size of .12, using Pearson r statistic) and that the effect size increased with age (Ma & Kishor, 1997). Subsequent publications supported this relationship, with significant positive correlations between ATM and math achievement reported across different grades and countries, including fifth-grade students in Cyprus (Nicolaidou & Philippou, 2003), and Grades 5 to 12 students in Portugal (Mata, Monteiro, & Peixoto, 2012). Similarly, ATM in middle school students from the United States and Belarus explain variance in math grades, with much of the explained variance independent of math skill (Lipnevich, Maccann, Krumm, Burrus, &

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Roberts, 2011). ATM are longitudinally predictive of math performance. Mazzocco, Hanich, and Noeder (2012) assessed Grades 2 and 3 students' definitions of mathematics in spontaneous conversations to assess their early beliefs about math (i.e., likeability, difficulty, and usefulness). Children's math definitions at Grade 2 predicted math calculation scores at Grade 3. Together, this work suggests that ATM has potential utility for predicting math outcomes.

Evidence altogether suggests that attitudinal aspects have an important impact on math performance. Another central factor that relates to performance on math tasks is prior math skill (O'Conner & Miranda, 2002). Especially in elementary school years, math performance is reliant upon children's math skills that develop in earlier years, such as linear representation of number, understanding principles of counting, basic arithmetic, and so forth (Jordan & Levine, 2009). Of special relevance here, however, is how attitudes interact with math skill to affect performance. This interaction is key to understand, because a person may have the competency to perform a task, but not necessarily desire to perform the task correctly. Conversely, positive attitudes without a certain level of skill might not guarantee performance success. Unfortunately, very little attention has been paid to this interaction and its impact on math performance.

How ATM and math skill interact in young children's math performance remains unexamined. Existing work examining interactions with skill focused on the role of motivation. Motivations and attitudes have been shown to independently contribute to math performance, but motivation also significantly predicts attitudes (Singh et al., 2002). Academic motivation can be defined as the degree to which individuals enjoy school learning without receipt of external rewards (Gottfried, Marcoulides, Gottfried, Oliver, & Guerin, 2007). DeMars (1999) studied how the interaction between motivation and skill predicted math performance. Two hundred forty-nine college students took a multiple-choice test assessing their mathematics and science performance. Verbal and math SAT data, which were available from admission records, were used as measures of skill. Students also took a short survey measuring their motivation, such as the perceived importance of the test. Both motivation and skill were significant predictors of task performance while controlling for the other. The skill by motivation interaction also predicted performance when entered in the model. This interaction showed that, although motivation was related to performance at all skill levels, relationship was somewhat less for the low-skill group, with higher motivation being associated with test scores to a greater extent for the high-skill group (DeMars, 1999). In contrast, Logan and colleagues' work showed that although intrinsic reading motivation for the low-skill group explained a significant amount of variance in reading comprehension performance, it did not explain a significant amount of variance for the high-skill group (Logan, Medford, & Hughes, 2011). These findings were interpreted as showing that children with low reading skills but higher motivation may have persevered and invested more effort on difficult materials. In contrast, their low-motivated peers may have been less engaged in developing their reading skills across time points. Overall, although motivation and attitudes are related but distinct constructs, the prior literature primarily only focused on how motivation interacts with skill. How attitudes interact with math skill in predicting math performance remains unexplored.

To our knowledge, no behavioral study has examined the interaction between ATM and math skill in young children's math performance. Furthermore, prior literature relied on behavioral performance that reflects the outcome of multiple component processes. Neuroimaging measures might help disentangle these multiple components at the neurocognitive level, and therefore provide more precise information about the interaction between math skill and ATM. The main objective of this study was to investigate the effects of the interaction between math skill and ATM on the brain correlates of a multiplication task in children, by means of functional magnetic resonance imaging (fMRI). The neural correlates of this interaction are, to the best of our knowledge, not known. We focused on multiplication, because of the four basic arithmetic operations, multiplication is the one that most heavily relies on memory-based retrieval strategies (Ischebeck et al., 2006; Prado, Mutreja, & Booth, 2014). Prior research in mathematics showed activation in memory-related brain circuits during retrieval strategy use as well as associations between self-perceived abilities and enhanced memory performance (Kao, Davis, & Gabrieli, 2005; Valentijn et al., 2006). A recent study examining the effect of ATM on the neurocognitive basis of addition similarly showed that positive ATM are associated with use of retrieval strategies (Chen et al., 2018).

Multiplication processing recruits the left middle temporal gyrus (MTG) and the left inferior frontal gyrus (IFG; Peters & De Smedt, 2018; Prado et al., 2011). Neuroimaging studies comparing multiplication with other math tasks suggested that multiplication facts are stored in the left MTG, which is considered to house the semantic associations between multiplication problems and their solutions (Prado et al., 2014; Prado et al., 2011). Participants' level of math skills relates to multiplication-related activity in left temporo-parietal cortex areas (e.g., left MTG). Greater activation of temporo-parietal areas is associated with more robust storage of arithmetic facts in long-term memory (Zamarian, Ischebeck, & Delazer, 2009). Similarly, a recent study showed greater activation for older compared with younger children in the left MTG during multiplication, which was interpreted as increased strength of semantic associations between problems and their solutions with more years of formal math education (Prado et al., 2014). This verbal area also shows decreased activation when children with math difficulty solve simple multiplication problems, suggesting impairment of the arithmetic fact retrieval mechanism (Berteletti, Prado, & Booth, 2014). Furthermore, during multiplication, mathematically more competent individuals display stronger activation in the brain areas related to fact retrieval (in this case, angular gyrus) than their less competent peers (Grabner et al., 2007).

The left IFG is considered to be involved in the effortful control and retrieval of semantic knowledge (Bookheimer, 2002) and be critical for selecting between active representations (Badre & Wagner, 2007). In contrast to the developmental increases in MTG, activation in the IFG during multiplication problem solving decreases with age (Prado et al., 2014). These findings have been interpreted as a developmental shift in brain areas underlying multiplication problem solving such that with increasing experience there is less need for cognitive control and greater reliance on direct retrieval from semantic memory (Prado et al., 2014). Similar findings have been reported using other math tasks, such as simple sums verification, where children showed greater IFG activation as compared with adults (Rivera, Reiss, Eckert, & Menon, 2005).

In the field of math cognition, only one study has investigated the impact of ATM on the brain (Chen et al., 2018). This study showed that positive attitudes were associated with increased engagement of the learning-memory systems in the medial temporal lobe, including the hippocampus, but not the affective-motivational systems in the ventral striatum and the amygdala. Furthermore, hippocampal activity and efficient use of memory-based strategies mediated the relation between ATM and skill. However, this study primarily focused on domain-general affective-motivational and learning-memory systems in the brain, and did not examine task-relevant activation in the areas that support arithmetic processing, such as the MTG and IFG. It also did not examine the possible interactions between ATM and math skill.

The major aim of this study was to investigate the interaction between math skills and ATM both behaviorally and at the neural level. ATM may in part predict math outcomes because negative attitudes are associated with avoidance of math and enrollment in mathematical courses (Aiken, 1970; Reynolds & Walberg, 1992). On the flip side, Hemmings and Kay (2010) found a significant positive relationship between attitudes and effort (r = .55), showing that the more positive those attitudes were, the more effort students invested. "In the face of difficulties, people who entertain serious doubts about their capacities slacken their efforts or give up altogether, whereas those who have a strong sense of efficacy exert greater effort to master the challenges" (Bandura, 1982, p. 25). Effort and time on task both relate to performance (Fisher & Ford, 1998). Holding positive attitudes toward a class might be related to investing more effort in that class.

Based on the above-mentioned studies investigating the interaction between attitudes and skill at a behavioral level, two possible divergent results were predicted. First, it might be the case that ATM would only affect the low-skill group (in line with Logan et al., 2011). By being more engaged in the task and investing greater effort, the low skill–positive attitudes group may show greater left IFG activation than the low skill–negative attitudes group. As a result, by engaging this frontal area more, this group may achieve a comparable level of performance as their high-skilled peers. On the contrary, differences in ATM could mainly affect the high-skill group (in line with DeMars, 1999). Despite having a high level of math skills, those with positive attitudes may have practiced more arithmetic facts and may have actively sought for opportunities to increase their math knowledge, leading to more precise representations of arithmetic facts in verbal memory. This prediction would be supported by finding greater MTG activation as well as less IFG involvement for the high skill–positive attitudes group, suggesting that arithmetic facts are better represented, and therefore, retrieval of their solution is less effortful than for the high skill–negative attitudes group.

Method

Participants

Seventy-seven children were recruited from schools in the greater Chicago, Illinois, area to participate in the study. All children (a) were native English speakers; (b) were free of past or present neurological or psychiatric disorders; (c) had no history of reading, oral language, or attention deficits; (d) scored higher than 80 standard score and lower than 140 standard score on full-scale IQ as measured by the *Wechsler Abbreviated Scale of Intelligence* (WASI; Wechsler, 1999); (e) could perform single-digit multiplication problems measured by the *Comprehensive Mathematical Abilities Test* (based on first 5 questions of the CMAT; Hresko, Schlieve, Herron, Swain, & Sherbenou, 2003); and (f) scored higher than 70 standard score and lower than 130 standard score on a timed math test as measured by Math Fluency subtest of the *Woodcock-Johnson Tests of Achievement* (Woodcock, McGrew, & Mather, 2001). Data from 18 participants were excluded because of excessive movement in the scanner (see criteria below), poor whole-brain coverage, low behavioral accuracy in the scanner (i.e., lower than 40%), response bias in the scanner (i.e., false alarm to misses ratio greater than 2 and false alarm rate greater than 50%), or performance outside the specified range on the standardized tests described above. The remaining 59 participants from 9 to 12 years of age were included in the analyses (29 girls, mean age = 11.2, SD = 1.2, range = 9–12.9). Written consent was obtained from the children and their parents/guardians. The Institutional Review Board at Northwestern University approved all experimental procedures.

Standardized Measures

Children were administered standardized measures to assess their intellectual ability, mathematical skills, and ATM. IQ was measured by the Verbal (Vocabulary, Similarities) and Performance (Block Design, Matrix Reasoning) subtests of the WASI. Reliability estimates for WASI subtests are between .86 and .96. Mathematical skills were measured by the Math Fluency subtest of the *Woodcock-Johnson III Tests of Achievement* (WJ-III, Woodcock et al., 2001). The Math Fluency subtest requires children to solve as many simple addition, subtraction, and multiplication problems as possible within a 3-min period. Reliability estimates for WJ-III subtests are between .84 and .94. To make sure that children have a basic understanding of single-digit multiplication problems on an untimed test, multiplication skill was assessed with the Basic Calculations subtests of the CMAT. Reliability estimates for CMAT subtests exceed or round to .90. Children's ATM were measured by the ATM subtest of the *Test of Mathematical Abilities–Third Edition* (TOMA-3, Brown, Cronin, & Bryant, 2012). The ATM subtest included 15 items related to children's liking or disliking of math (e.g., "I've always liked math"), their tendency to avoid math (e.g., "I'd rather do math than any other kind of homework"), how useful they thought studying math is (e.g., "There's no reason to take math every year"), how good they thought they were on math (e.g., "Math tests are usually easy for me"), or general ideas about math being interesting or exciting (e.g., "Math is interesting and exciting"). Children were presented with the above-mentioned statements about math and were asked to choose among four options ranging from *yes definitely* to *no definitely* (Cronbach's $\alpha = .86$). Standardized scores were used for all measures.

fMRI Task: Multiplication

Participants were presented with single-digit multiplication problems. In each trial of the multiplication task, children were asked to evaluate whether the answer to a single-digit multiplication problem was true or false. Twenty-four number pairs were used, covering the full range of single-digit multiplication problems (with the exceptions below). Twelve "small" and 12 "large" problems were included in the task. Operands of small problems were smaller than or equal to 5 (e.g., 3×4). Operands of large problems were larger than 5 (e.g., 6×7). Each pair was repeated twice with a true answer (e.g., $3 \times 4 = 12$) and once with a false answer. Thus, children were presented with 72 problems in total. False answers were created by replacing the correct answer by the answer that would have been obtained by adding or subtracting 1 from the first operand (e.g., $3 \times 4 = 16$). Problems with 0 as an operand (e.g., 3×0), problems with 1 as an operand (e.g., 3×1), and tie problems where the first and second operand are identical (e.g., 3×3) were not used in the main experiment, but were used in the practice sessions to familiarize the children with the task. Twenty-four problems were used in the practice sessions.

Experimental Procedure

First, informed consent was obtained and standardized tests were administered. The children then learned to minimize their head movement in a mock fMRI scanner (with feedback from an infrared tracking device). To ensure that children understood all the tasks and were familiarized with the fMRI environment, they practiced the multiplication task in the mock fMRI scanner. The actual fMRI scanning session took place within 1 week of the practice session. In the fMRI scanner, children were presented with single-digit multiplication problems (see Note 1). The multiplication task was divided into two runs of about 4 min each. Behavioral responses were recorded using an MR-compatible keypad placed below the right hand. Visual stimuli were generated using E-prime software (Schneider, Eschman, & Zuccolotto, 2002), and projected onto a translucent screen. Children viewed the screen through a mirror attached to the head coil.

Stimulus Timing

A trial started with the presentation of a first stimulus (multiplication problem) for 800 ms, followed by a blank screen for 200 ms. A second stimulus (multiplication answer) was presented for 800 ms, followed by a red fixation square presented for 200 ms. The red square indicated that the participant was required to make a response during an interval ranging from 2,800 ms to 3,600 ms (see Figure 1). Twenty-four null trials were included. In the null trials, a blue square was presented for the same duration as the experimental conditions and children were asked to press a button when the square turned red. The timing and order of trial presentation within each run was optimized for estimation efficiency using Optseq2 (see http://surfer.nmr.mgh.harvard.edu/optseq/).

fMRI Data Acquisition

Images were collected using a Siemens 3T TIM Trio MRI scanner (Siemens Healthcare, Erlangen, Germany) at the Center for Translational Imaging at Northwestern University. The fMRI blood oxygenation level-dependent (BOLD) signal was measured with a susceptibility weighted single-shot echo planar imaging (EPI) sequence. The following parameters were used: TE (echo time) = 20 ms, flip angle = 80°, matrix size = 128×120, field of view = 220×206.25 mm, slice thickness = 3 mm (0.48 mm gap), number of slices = 32, TR (repetition time) = 2,000 ms. Before functional image acquisition, a high resolution T1-weighted three-dimensional (3D) structural image was

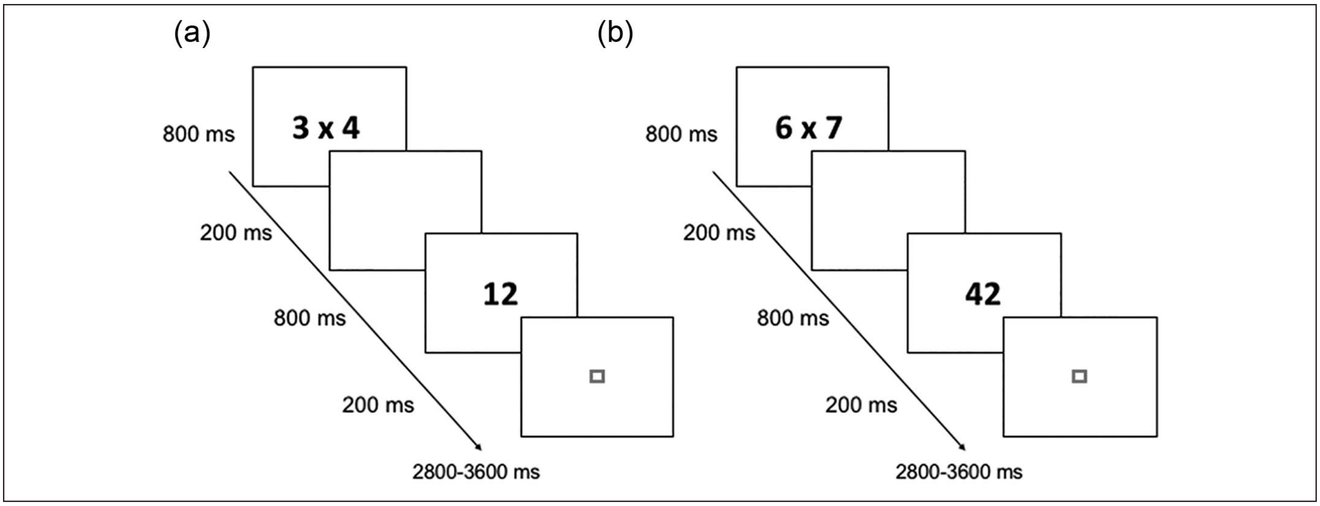

Figure 1. Experimental task in which participants were asked to verify the answer to (a) small (smaller than or equal to 5) and (b) large (larger than 5) multiplication problems.

acquired for each subject (TR = 1,570 ms, TE = 3.36 ms, matrix size = 256 × 256, field of view = 240 mm, slice thickness = 1 mm, number of slices = 160).

fMRI Preprocessing

Data analyses were performed using SPM8 (Statistical Parametric Mapping; see www.fil.ion.ucl.ac.uk/spm). The first six images of each run were discarded, functional images were corrected for slice acquisition delays, realigned to the first image of the first run to correct for head movements, and spatially smoothed with a Gaussian filter equal to about twice the voxel size ($4 \times 4 \times 8$ mm^3 full width at half maximum). Prior to normalization, ArtRepair software (Mazaika, Hoeft, Glover, & Reiss, 2009; see https://cibsr.stanford.edu/tools/human-brain-project/artrepair-software.html) was used to suppress residual fluctuations due to large head motion and to identify volumes with significant artifact and outliers relative to the global mean signal (i.e., 4% from the global mean). Volumes showing rapid scan-to-scan movements of greater than 1.5 mm were excluded via interpolation of the two nearest nonrepaired volumes. All participants had less than 5% of the total number of volumes replaced in a single run and less than four volumes replaced in a row. Interpolated volumes were partially deweighted when first-level models were calculated on the repaired images (Mazaika et al., 2009). Functional volumes were co-registered with the segmented anatomical image and normalized to the standard T1 Montreal Neurological Institute (MNI) template volume (normalized voxel size, $2 \times 2 \times 4$ mm^3).

fMRI Data Analysis

First-level analysis. Event-related statistical analyses were performed according to the General Linear Model. Activation was modeled as epochs with onsets time-locked to the presentation of the first stimulus and with a duration matched to the length of the trial (2 s). All children's responses were included in the model, but only their responses to problems with a proposed true answer were considered of interest in the analyses. This was done to exclude brain activation due to error detection. All epochs were convolved with a canonical hemodynamic response function. The time series data were high-pass filtered (1/128 Hz), and serial correlations were corrected using an autoregressive AR(1) model. Effect sizes were estimated using linear statistical contrasts and subsequently entered into second-level analyses.

Second-level analysis. To evaluate the relationship among math skills, ATM, and neural bases of multiplication, second-level voxel-wise regression models were created. In each analysis, math skills and ATM, as well as the interaction between the two, constituted the regressors of interest. For the second-level analyses, we divided children into two groups based on their math attitudes score as measured by TOMA (negative vs. positive) using a median split. Similarly, children were divided into two groups based on their math skills as measured by Woodcock-Johnson Fluency (low vs. high) using a median split. We also included full-scale IQ as an additional regressor. The analyses were conducted separately for each problem type (small, large). To examine the relationship between math skills or attitudes and the neural bases of arithmetic, we identified the brain regions that showed an increase or a decrease in activity during the evaluation of small or large multiplication problems with respect to math skills or attitudes across participants. To evaluate if math attitudes moderated the relationship between math skills and the neural bases of arithmetic, we identified brain regions that showed an interaction term across participants. For all analyses, an implicit baseline of general task activation was used, which included activation not modeled, that is, blank screen between trials and fixation point breaks, and excluded activation linked to model regressors (small and large problems with true answers and null trials). All analyses were repeated with measures of accuracy and response time (RT) on the multiplication task solved inside the scanner as additional regressors and the results reported below remained unchanged.

Region of interest (ROI) definition. We first identified brain regions that revealed greater activation during multiplication problems using the [all multiplication – baseline] contrast. This contrast was submitted to one-sample t tests across all participants. The resulting statistical maps were thresholded for significance (using a voxel-wise height threshold of $p < .01$, FWE [family-wise error]-corrected cluster wise threshold of $p < .05$). Based on previous literature and our specific hypotheses, an anatomical mask consisting of IFG and MTG of the left hemisphere was used to constrain activations associated with the multiplication task (Booth, 2010). The anatomical masks were defined using the conventional AAL (Automated Anatomical Labeling) atlas. The ROI consisted of one cluster in the left IFG (peak coordinate: $x = -52$, $y = 13$, $z = 30$, BA = 44, $z = 5.58$, size = 906 voxels) and a cluster in left MTG (peak coordinate: $x = -62$, $y = -37$, $z = 2$, BA = 21, $z = 4.64$, size = 307 voxels; see Supplemental Figure 1).

Statistical significance for the resulting functional + anatomical mask was defined using Monte Carlo simulations using AFNI's 3dClustSim program (December, 2015; see http://afni.nimh.nih.gov/, with SPM's data smoothness parameters, autocorrelation function [ACF] = 0.42, 4.42, 9.99). 3dClustSim carries out a user-specified number of Monte Carlo simulations of random noise activations at a particular voxel-wise alpha level within a masked brain volume. Following the suggestions made by Eklund, Nichols, and Knutsson's (2016) recent article regarding the inflated statistical significance achieved using some packages (i.e., SMP, FSL and AFNI), we used 3dClustSim's most recent version (December 2015). We used 3dFWHMx to calculate the smoothness of the data for every single participant (as compared with previously used FWHMxyz values), using a spatial ACF, and then averaged those smoothness values across all participants. This average smoothness value was then entered into 3dClustSim to calculate the cluster size needed for significance for a given ROI. Clusters exceeding these size thresholds were deemed significant. For the ROI, to reach corrected level threshold ($\alpha = .05$), with a voxel-level p value of .05, a cluster size of 70 voxels was required.

Whole-brain analysis. To investigate nonpredicted effects in regions outside the ROIs, we also report results of whole-brain analysis. Statistical significance for the whole brain was also defined using Monte Carlo simulations (using AFNI's 3dClustSim program, ACF = 0.42, 4.42, 9.99). For the whole-brain analysis, to reach corrected level threshold ($\alpha = .05$), with a voxel-level p value of .05, this required 1,360 voxels.

Results

Behavioral Results

Descriptive statistics for the behavioral measures are provided in Table 1. Children were divided into two groups based on their ATM scores as measured by the TOMA (negative vs. positive) using a median split. Similarly, children were divided into two groups based on their math skill as measured by Woodcock-Johnson Fluency (low vs. high skill) using a median split. As expected, children in the negative ATM group had significantly lower math attitude scores than children in the positive ATM group, $t(57) = 12.62$, $p < .001$. Similarly, children in the low-skill group had significantly lower math skill scores than children in the high-skill group, $t(57) = 11.42$, $p < .001$. Nineteen of the 30 children who had negative ATM also had low skills, and 13 of 29 children with positive ATM also had low math skills. Chi-square analyses showed that there was no significant association between skill and ATM, $\chi^2 = 2.04$, $p = .15$. Thus, the number of children who had negative versus positive ATM did not vary by skill. Distribution of females did not significantly vary according to group, $\chi^2 = .84$, $p > .05$.

We ran 2 × 2 ANOVAs using ATM (negative vs. positive) and skill (high, low) as independent variables, and age, accuracy, and reaction time on in-scanner multiplication task, CMAT composite score, CMAT multiplication subtest score, and WASI full-scale IQ as dependent measures. Children with high math skill performed significantly more accurately on multiplication problems inside the scanner, $F(1, 55) = 16.62$, $p < .001$, $\eta_p^2 = 0.23$. There were also trends for high math skill children to solve multiplication problems faster inside the scanner, $F(1, 55) = 3.01$, $p = .09$, $\eta_p^2 = 0.05$, and to perform better on the CMAT standardized test outside the scanner, both on the multiplication subtest, $F(1, 55) = 3.22$, $p = .08$, $\eta_p^2 = 0.06$ as well as on the overall composite, $F(1, 55) = 3.74$, $p = .06$, $\eta_p^2 = 0.06$. Children with negative ATM did not significantly differ from their peers with positive ATM on multiplication accuracy and reaction time inside the scanner, all ps > .05, although they were significantly less accurate on the CMAT standardized test, both on multiplication, $F(1, 55) = 4.21$, $p = .05$, $\eta_p^2 = 0.07$ and the overall composite score, $F(1, 55) = 6.55$, $p = .01$, $\eta_p^2 = 0.11$. Skill and ATM were not associated with age or IQ, all ps > .05.

Most importantly for our purposes, there was no significant interaction between ATM and skill on accuracy or RT inside the scanner, all ps > .05, so any interactions between

Table 1. Means, Standard Deviations, Ranges for Children's Scores on the Standardized Tests, and In-Scanner Performance in the Multiplication Task, as Function of Math Skills and ATM.

	Low-skills group		High-skills group		
Measure	Negative ATM	Positive ATM	Negative ATM	Positive ATM	Average
Age (in years)	11.3 (1.2) 9.3–12.9	11.5 (0.9) 9.5–12.8	11.9 (0.9) 9.5–12.9	10.4 (1.1) 9.1–12.7	11.2 (1.2) 9.1–12.9
No of girls/all children	7/16	5/12	5/12	12/19	29/59
Standardized tests					
WASI IQ	106.5 (17.7) 83–136	110.6 (12.7) 95–129	102.8 (11.5) 83–120	117.6 (12.1) 96–136	109.4 (14.9) 83–136
WJ Math Fluency	83.9 (7.2) 76–98	88.5 (8.1) 74–96	109.3 (9.7) 100–130	112.8 (9.2) 99–130	98.2 (15.5) 74–130
CMAT Multiplication	9.7 (3.1) 5–17	10.4 (1.9) 8–17	10.2 (3.6) 6–19	12.9 (3.2) 6–15	10.8 (3.3) 5–19
TOMA	7.2 (3.1) 1–11	16.1 (2.4) 12–19	7.3 (2.1) 4–11	14.94 (2.0) 12–18	11.0 (4.8) 1–19
Multiplication in-scanner measures					
Accuracy	72% (16%) 42%–97%	72% (12%) 52%–92%	89% (7%) 77%–99%	84% (13%) 60%–100%	79% (15%) 42%–100%
Reaction time (ms)	1,211 (327) 721–1,863	1,207 (232) 808–1,553	1,039 (384) 457–1,655	1,073 (343) 549–1,811	1,135 (331) 457–1,863

Note. Standard deviations in parentheses. Skill grouping was based on WJ-III Math Fluency (median split). ATM grouping was based on TOMA (median split). ATM = attitudes toward math; WASI = Wechsler Abbreviated Scale of Intelligence (Wechsler, 1999); WJ-III = Woodcock-Johnson III Tests of Achievement (Woodcock et al., 2001); CMAT = Comprehensive Mathematical Abilities Test (Hresko, Schlieve, Herron, Swain, & Sherbenou, 2003); TOMA = Test of Mathematical Abilities–Third Edition (Brown, Cronin, & Bryant, 2012).

these variables on brain activation data should not be due to performance differences. Simple effects did not reach significance either, all $ps > .05$. We also did not observe significant ATM and skill interactions on the composite or multiplication measures from the CMAT. However, simple effects analyses showed that children with low skill but positive ATM had marginally significantly higher composite CMAT scores than their peers with low skill and negative ATM on the composite score, $t(28) = 1.75$, $p = .09$. Similarly, children with high skill and positive ATM had significantly higher CMAT multiplication scores, $t(27) = 2.15$, $p = .04$, and marginally significantly higher CMAT composite scores than their peers with high skill but negative ATM, $t(27) = 1.88$, $p = .07$. There was no significant interaction between ATM and skill on IQ or on age, all $ps > .05$, suggesting that the groups were matched on these variables.

Neuroimaging Results

Overall brain activation during the multiplication task. We first examined overall activation during the multiplication task, using contrast of [small trials – baseline] and [large trials – baseline] submitted to one-sample t tests across all participants. For small problems, we saw activation in a cluster in the left MTG (peak coordinate: $x = -56$, $y = -47$, $z = 10$, BA $= 21$, $z = 4.74$, size $= 307$ voxels) and a cluster in the left IFG (peak coordinate: $x = -50$, $y = 13$, $z = 26$, BA $= 44$, $z = 5.07$, size $= 878$ voxels). For large problems, we saw activation in a cluster in the left MTG (peak coordinate: $x = -62$, $y = -37$, $z = 2$, BA $= 21$, $z = 4.11$, size $= 216$ voxels) and a cluster in the left IFG (peak coordinate: $x = -52$, $y = 13$, $z = 30$, BA $= 44$, $z = 5.62$, size $= 905$ voxels). The peak coordinates of left IFG and MTG were close to coordinates identified in previous studies using the same multiplication task (Euclidian distance of less than 15 mm; Berteletti et al., 2014; Prado et al., 2011).

Relationship between math skills and brain activation. We then examined if activation in the ROIs during the multiplication task varied as function of children's math skills. First we examined if math skills was differentially related to small versus large problems using the [large trials – small trials] contrast. We did not observe a relationship between math skills and this contrast. We then explored the relationship between the interaction term for ATM × Skill and small and large problems separately. For small problems, we saw a negative relation between math skill and activation in a cluster in left IFG (peak coordinate: $x = -42$, $y = 23$, $z = 30$, BA $= 9$, $z = 3.48$, size $= 239$ voxels). For large problems, we saw a negative relationship between math skill and activation in an overlapping cluster in left IFG (peak coordinate: $x = -42$, $y = 23$, $z = 30$, BA $= 9$, $z = 3.29$, size $= 264$ voxels). We did not observe any positive relations between math skill and activation in our ROIs (see Supplemental Figure 2A).

Relationship between ATM and brain activation. We then examined if activation in the ROIs during the multiplication task varied as a function of children's ATM. First, we examined if ATM were differentially related to small versus large problems using the [large trials – small trials] contrast. We saw a negative relation of ATM to activation in the left IFG for this contrast (peak coordinate: $x = -48$, $y = 11$, $z = 18$, BA = 44 $z = 2.49$, size = 99 voxels). We then explored the relationship between ATM and small and large problems separately. For small problems, we saw a negative relationship between ATM and activation in two clusters in the left IFG, one located dorsally (peak coordinate: $x = -36$, $y = 35$, $z = 26$, BA = 9, $z = 3.96$, size = 210 voxels) and another located more ventrally (peak coordinate: $x = -56$, $y = 11$, $z = 22$, BA = 44, $z = 3.20$, size = 85 voxels). We did not observe any positive relationships between ATM and activation in our ROIs for small problems. For large problems, we did not observe positive or negative correlations between ATM and brain activation in the ROIs (see Supplemental Figure 2B).

Relationship between math skill and brain activation as a function of ATM. We then examined our main question: Would activation in the ROIs during the multiplication task show an interaction between children's math skills and ATM. First, we examined if the interaction term was differentially related to small versus large problems using the [large trials – small trials] contrast. We saw a relationship to the interaction term in the left IFG for this contrast (peak coordinate: $x = -49$, $y = 7$, $z = 10$, BA = 44, $z = 2.36$, size = 68 voxels), which fell two voxels short of significance. When we examined small and large problems separately, we found an interaction for small problems in the left IFG, specifically in pars opercularis (peak coordinate: $x = -38$, $y = 21$, $z = 30$, BA = 9/44, $z = 3.01$, size = 124 voxels; see Supplemental Figure 2C).

We extracted the average beta weight from the significant cluster and graphed it as a function of math skill (low, high) and ATM (negative, positive). Figure 2 shows that the interaction was driven by children with low skills but positive ATM activating left IFG to a greater extent than low skills, negative ATM children. High-skills children did not differ from each other in the left IFG activation as a function of ATM. This visual pattern was confirmed by a simple effect analysis showing that low skill, positive ATM children had greater activation of the left IFG than low skill, negative ATM children (peak coordinate: $x = -36$, $y = 35$, $z = 26$ BA = 9, $z = 3.63$, size = 72 voxels). The simple effects analysis comparing IFG activation in negative versus positive ATM children among the high-skills group did not reveal significant differences. Similarly, for large problems, we did not observe any significant interactions in the ROIs.

Whole-brain analysis. Outside the ROIs, the interaction term (Math Skills × ATM) was significant and positively related to activation in two clusters for small problems. One spanned the left cingulate, insula and extending into right lingual gyrus (peak coordinate, $x = -16$, $y = -59$, $z = 6$, BA = 23/19/13, $z = 3.78$, $k = 9{,}673$ voxels) and the other included the right middle frontal gyrus (peak coordinate, $x = 30$, $y = 1$, $z = 38$, BA= 6/8, $z = 3.52$, $k = 2{,}095$ voxels). For large problems, the interaction term (Math Skills × ATM) was significant and positively related to activation in two similar clusters to the small problems, including left postcentral gyrus and right posterior cingulate/calcarine gyrus (peak coordinate, $x = -38$, $y = -23$, $z = 46$, BA = 1/3/23/30, $z = 4.42$, $k = 5{,}377$ voxels) and middle and superior frontal gyrus extending into precentral gyrus (peak coordinate, $x = 34$, $y = 7$, $z = 38$, BA = 6/8/9, $z = 3.7$, $k = 1{,}610$ voxels).

Discussion

The main objective of this study was to investigate the interaction between math skills and ATM on two of the brain areas associated with single-digit multiplication task performance identified in previous fMRI studies, the left MTG, and the left IFG (Peters & De Smedt, 2018; Prado et al., 2014, 2011). Regarding the main effects of skills, we found a negative relationship between math skill and left IFG activation both for small and large problems. Left IFG is involved in the effortful control and retrieval of semantic knowledge (Bookheimer, 2002) and is considered critical for selecting between active representations (Badre & Wagner, 2007). In the context of arithmetic, the left IFG is associated with the effort spent in retrieving and selecting the solutions from verbal memory (Prado et al., 2014). Our results suggest that when solving multiplication problems, high-skills children might retrieve and select the solution from memory less effortfully than low-skill children. This finding is consistent with prior work showing that left IFG activation decreases with age during multiplication problem solving. This developmental decrease is interpreted as reflecting less need for cognitive control over time as the connections between a problem and its correct solution in MTG become stronger with math instruction (Prado et al., 2014).

As for the main effect of ATM, we found a negative relationship between math attitudes and left IFG activation for small problems. The peak for one of the clusters for the association with ATM overlapped with the peak of main effect of skills (Euclidian distances of less than 15 mm), but the other cluster extended more ventrally. Studies in the field of language suggested that the ventral left IFG is more

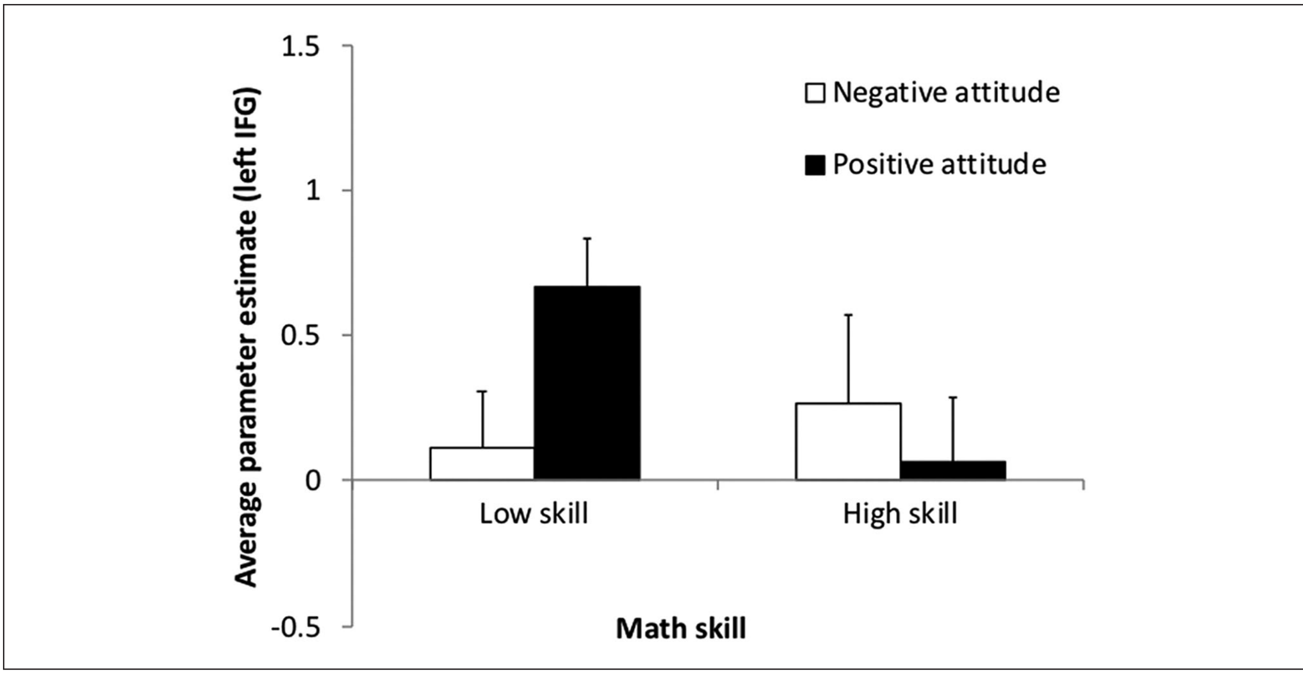

Figure 2. Average parameter estimate in the left IFG for small multiplication problems as a function of math skill (low, high) and ATM (negative, positive) (note that this figure is for illustrative purposes only).
Note. IFG = inferior frontal gyrus; ATM = attitudes toward math.

heavily involved in semantic processing and retrieval. Dorsal left IFG is considered to be a domain-general control area involved in working memory functions (Arsalidou & Taylor, 2011; Kaufmann, Wood, Rubinsten, & Henik, 2011; Yarkoni, 2014). Dorsal left IFG is activated in the selection of specific aspects of knowledge in line with an externally specified goal (Badre, Poldrack, Paré-Blagoev, Insler, & Wagner, 2005). Multiplication problem solving involves *retrieving* different alternative solutions in long-term memory, which may rely on ventral IFG, and requires *selecting* the correct solution among the alternatives, which may rely on dorsal IFG. Our findings suggest that while both math skill and ATM are associated with selecting the correct solution from long-term memory by engaging dorsal left IFG, only ATM are associated with semantic retrieval through recruitment of ventral left IFG.

The fact that children with positive ATM engage left IFG to a lesser degree suggests that retrieval of solutions might be less effortful for them. Children with positive ATM may have been more engaged in math classes, may have practiced arithmetic facts more frequently, and have actively sought out opportunities to practice multiplication problems. Given the relationship between ATM and math avoidance (Aiken, 1970; Reynolds & Walberg, 1992), children with positive ATM may have not avoided situations involving math or numeric stimuli (as compared with their negative ATM peers) and might have had greater exposure to math content. Lower skills in multiplication, at the age range we examined, might be more tightly linked to domain-general demands, such as selection of a correct response among multiple retrieved responses. Supporting this view, in adults, untrained multiplication problems activate dorsal left IFG to a greater extent, reflecting higher working memory demands of the former set of problems than trained problems (Delazer et al., 2003).

More importantly, our results showed that the neural basis of multiplication varies depending on both math skill and ATM. Among children with lower math skills, positive ATM were associated with greater activation of the left IFG when children solved small multiplication problems. This is in line with previous evidence suggesting that motivational factors do not equally affect all skill levels (DeMars, 1999; Logan et al., 2011). Why might children with lower math skills but positive ATM engage left IFG to a greater degree than those with negative ATM? Previous work has linked positive ATM with the investment of more effort in math tasks (Hemmings & Kay, 2010) and positive self-efficacy beliefs with effort and perseverance (Bandura, 1982). Higher left IFG activation might reflect low skill–positive ATM children investing greater effort on the task. More specifically, the peak of this interaction effect overlapped with the peak of the cluster of the skill effect (Euclidian distances of less than 15 mm) in the dorsal part of the left IFG. Because the dorsal part of the left IFG is involved in the selection of specific aspects of knowledge (Badre et al., 2005), we interpret our findings as suggesting that the low skill–positive ATM subgroup invested more effort in selecting the correct solution for the multiplication problems from among the alternatives. In addition, the interaction between attitude and skills was modulated by difficulty level of the task. The interaction was observed for small problems but not for large problems. This might be because math skills and ATM only interact when tasks are relatively easy for the learner. When tasks are far above the child's skill level, the low skills might wash out any possible positive effects of attitudes.

We did not find any significant interaction between ATM and skills on either the scanner task performance (accuracy or RT) or standardized measures outside the scanner. Thus, the low skills–positive ATM group's greater IFG activation did not result in better performance than the low skills–negative ATM group. Although null results are difficult to interpret, this finding is consistent with the findings of a meta-analysis showing that the effects of ATM on performance are significant but not strong (effect size of .12; Ma & Kishor, 1997). Moreover, the relationship between ATM and performance varies with grade and becomes stronger among older students (Grades 7–12; Ma & Kishor, 1997). Thus, the lack of significant effects of ATM on performance in our study might be due to our sample consisting of younger 9- to 12-year-old children. Furthermore, the bulk of studies assessing the relationship between ATM and math performance used academic achievement (i.e., math course grades) as a measure of performance (e.g., Lipnevich et al., 2016; Mata et al., 2012). It is reasonable that groups did not differ in scanner performance, because the scanner task was designed to examine the brain basis of arithmetic, rather than individual differences in performance. We did not have more ecologically valid measures of math performance such as math grades or performance on math achievement tests solved in class context. Of special interest would be to use longitudinal studies to address whether the predictive effect of ATM on subsequent performance is limited to one of the skill groups. For example, greater IFG activation shown by the low skill–positive ATM group in this study might predict better performance in the task later in time. In other words, this greater investment of effort, reflected by the greater IFG activation, might not immediately translate into better performance, but might show its positive effects later in time.

Although we did not find a significant interaction between ATM and skills on the CMAT, negative ATM children performed numerically worse on this test than their peers with positive ATM. Furthermore, when we specifically compared the CMAT scores of low skill–positive ATM and low skill–negative ATM subgroups, we found a trend for the former group to have higher CMAT scores than the latter. This suggests that the greater effort in the low skill–positive ATM group, as reflected in higher left IFG activation, might indeed be related to better math performance, and this relationship might be greater when a task is untimed. Although this result should be taken with caution, it would be in line with previous evidence, in the field of reading, suggesting that intrinsic motivation is associated with better reading performance only for low-skill readers (Logan et al., 2011).

Although we leveraged a multiplication task, whether these results extend to other arithmetic tasks that rely on different networks, such as subtraction, should be examined in future studies. We decided to study multiplication problems because positive attitudes influence memory-based strategies and systems in learning (Kao et al., 2005; Valentijn et al., 2006), and of the four basic arithmetic operations, multiplication is the one that most heavily relies upon memory-based retrieval strategies. The results from both our study and a recent study examining the role of ATM in the neural basis of addition (Chen et al., 2018) suggest that ATM might play a role in retrieval-based strategies. Whether these results are generalizable to other kinds of problems, such as subtraction, which relies more on quantity manipulation strategies and less on retrieval, is open for discussion.

We did not observe a main effect of ATM or a math skills-by-ATM interaction in the left MTG. Multiplication-related activity in left temporo-parietal cortex areas is dependent on the participants' level of expertise. Greater temporo-parietal activation is found for children with more years of mathematical instruction (Prado et al., 2014), for individuals more competent in math (Grabner et al., 2007), and for those with a greater number of arithmetic facts stored in long-term memory (Zamarian et al., 2009). The lack of findings in temporo-parietal cortex possibly suggests that ATM do not affect how precisely math facts are represented in verbal memory. Rather, ATM seem to influence the controlled effort and retrieval of multiplication facts, as revealed in greater activation in left IFG for low skill–positive ATM children compared with their peers. However, null findings are hard to interpret, because they could occur due to a multitude of reasons, such as low power. Indeed, a recent study on younger children examining the effect of ATM on neurocognitive basis of addition revealed that ATM are associated with greater engagement of hippocampal areas, which in turn is related to retrieval rate (Chen et al., 2018). Hippocampus, however, plays a role in initial stages of learning arithmetic facts (De Smedt, Holloway, & Ansari, 2011). Thus, the relationship between ATM and the neural systems associated might vary as children become more proficient in math.

Outside the verbal ROIs on which we focused, ATM by skills interactions were also observed in the insula and the cingulate cortex, as well as in the middle/superior frontal cortex. A rich body of literature has noted the involvement of the insula and the cingulate cortex in emotional processing, as well as specifically in attitudes and evaluations

(Cunningham & Zelazo, 2007; Phan, Wager, Taylor, & Liberzon, 2002). These areas are also involved in inhibitory processes and response selection (Criaud & Boulinguez, 2013; Zhang, Geng, & Lee, 2017). Middle and superior frontal areas are involved in working memory and executive function (D'Esposito et al., 1995). This general pattern of results highlights that domain-general processes—such as inhibitory control—emotional processes, and working memory processes might be involved in the interactions between ATM and math skills.

ATM are correlated with math anxiety (correlations around –.70; Hembree, 1990), which is defined as "a feeling of tension, apprehension or even dread that interferes with the ordinary manipulation of numbers and the solving of mathematical problems" (Ashcraft & Faust, 1994, p. 98). Chen and colleagues (2018) showed that ATM contributes to math performance even after controlling for math anxiety. We did not measure or control for this variable in our study. Although we did not find ATM-related differences in performance, some of our subgroups, like the low skill–negative ATM one, may have been affected by a negative emotional reaction while performing mathematical tasks. Prior work showed that among high-math-anxious adults, the more they engaged frontal areas before starting a math task, including the left IFG, the better they performed on the task (Lyons & Beilock, 2012). This finding might reflect ramping up of cognitive control resources when anticipating a math task, enabling high-math-anxious individuals to reduce their math anxiety and succeed in the task. Similarly, some of the left IFG activation we observed might be related to enhancing cognitive control to deal with math anxiety and to avoid performance from being negatively affected by this anxiety. Future work should measure ATM and math anxiety in the same study to examine their individual contributions and their possible role as mediators in the relationships to math performance.

Our study highlights the interactions between attitudinal and cognitive factors in math performance and its neural basis. Prior studies in educational neuroscience mostly focused on children's skill to explain children's mathematical performance. Here, we show that low-skills children are not a homogeneous group. Children with positive ATM might more fully engage the neurocognitive systems underlying controlled effort and retrieval of multiplication facts. Teachers and math educators agree that children learn more effectively when they are interested in what they learn and are highly motivated (Ma & Kishor, 1997). Moreover, ATM are relatively malleable (Lipnevich et al., 2016; Singh et al., 2002). Simple classroom interventions, such as working in cooperative groups where the students can help each other, are effective in improving students' ATM (Leikin & Zaslavsky, 1997). Furthermore, children's belief in malleability of math skills predicts better math performance (Blackwell, Trzesniewski, & Dweck, 2007). By attending to attitudinal factors and including plans for developing positive ATM in their students, teachers could positively impact the learning students get from math instruction.

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Note

1. Children were also administered subtraction, rhyming, and numerosity tasks in the same sessions, but these tasks are not included in this study.

Supplemental Material

Supplemental material for this article is available online.

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