

# Mathematics Anxiety: Separating the Math from the Anxiety

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**Anxiety about math is tied to low math grades and standardized test scores, yet not all math-anxious individuals perform equally poorly in math. We used functional magnetic resonance imaging to separate neural activity during the anticipation of doing math from activity during math performance itself. For higher (but not lower) math-anxious individuals, increased activity in frontoparietal regions when simply anticipating doing math mitigated math-specific performance deficits. This network included bilateral inferior frontal junction, a region involved in cognitive control and reappraisal of negative emotional responses. Furthermore, the relation between frontoparietal anticipatory activity and highly math-anxious individuals' math deficits was fully mediated (or accounted for) by activity in caudate, nucleus accumbens, and hippocampus during math performance. These subcortical regions are important for coordinating task demands and motivational factors during skill execution. Individual differences in how math-anxious individuals recruit cognitive control resources prior to doing math and motivational resources during math performance predict the extent of their math deficits. This work suggests that educational interventions emphasizing control of negative emotional responses to math stimuli (rather than merely additional math training) will be most effective in revealing a population of mathematically competent individuals, who might otherwise go undiscovered.**

**Keywords:** cognitive control, cognition and emotion, fMRI, math anxiety

## Introduction

Although basic math skills are important for everyday life, many people report feeling anxious when faced with the prospect of doing math. Mathematics anxiety is characterized by feelings of tension, apprehension, and fear about performing math and is associated with delayed acquisition of core math and number concepts and poor math competence (Richardson and Suinn 1972). Math anxiety is clearly an impediment to math achievement (Ashcraft and Ridley 2005; National Mathematics Advisory Panel 2008). However, not all people high in math anxiety perform equally poorly in math. This variation in math performance among the highly math anxious (HMAs) provides an opportunity (1) to understand the reasons for the negative relation typically seen between math anxiety and math competence, and (2) to shed light on how this relation is ameliorated.

In the current work, HMAs and a group of low math-anxious controls (LMAs) were identified via a common self-report measure of math-anxiety (Short Math-Anxiety Rating Scale [SMARS]; Alexander and Martray 1989). All participants performed a mental arithmetic task and difficulty matched word-verification task during functional magnetic resonance image (fMRI) acquisition. Crucially, before each set of problems, individuals were presented with a cue (a simple colored shape)

identifying the nature of the upcoming task (math or word). This paradigm, allowed us to separate neural activity underlying the anticipation of doing math from that of math performance itself.

As a preview, we found that HMAs' overall performance was characterized by a math-specific deficit: HMAs showed significantly poorer math performance relative to a non-math, difficulty-matched task (LMAs performed the same on both tasks—Fig. 1). Importantly, some HMAs showed more of a math deficit than others and these math deficits were not related to level of reported math anxiety. We thus asked whence this variation in math deficits among HMAs arises.

One possibility is that some HMAs are better at math than others. Such a finding would be in-keeping with assertions that math anxiety is merely a proxy for poor math competence (Fennema 1989); that is, people with the lowest math competence are most anxious about their lack of math proficiency. If so, then activity in neural regions important for numerical calculation (e.g., left intraparietal sulcus [IPS]; Simon et al. 2002) should relate to the extent of HMAs' math deficits. Moreover, this activity, which supports the successful retrieval and implementation of mathematical computations, should occur during math performance itself.

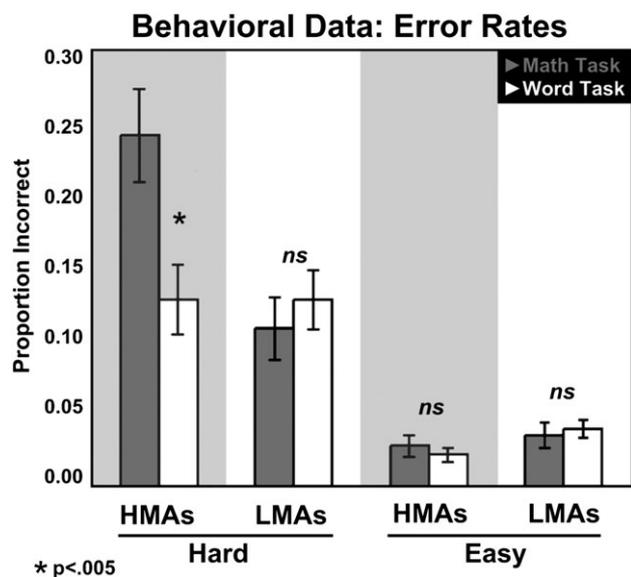
Another possibility is that the anxiety felt by HMAs changes how they approach math, and this in turn affects math competence. If so, then neural activity related to HMAs' math deficits may be apparent before the math task even begins. For example, the extent to which HMAs recruit regions related to attentional control and the reappraisal of negative emotions in response to a cue indicating that they are about to do math (e.g., regions such as midposterior dorsolateral prefrontal cortex [DLPFC]; Ochsner et al. 2004; Bishop 2007) might predict their math deficits. The more activity in these regions, the better HMAs may be at controlling their negative response to the upcoming math task. This, in turn, may allow for the coordination of the appropriate neural resources required to successfully perform the math task.

In sum, for the first time with math-anxious individuals, we were able to separate the neural correlates underlying the anticipation of doing math from those of math performance itself. Our findings shed light on the factors driving the comorbidity of math anxiety and poor math competence, knowledge needed to develop the appropriate educational interventions to ameliorate this relation.

## Materials and Methods

### Subjects

Subjects were 32 right-handed University of Chicago students (mean age = 20.47 years, range = 18–25). Math-anxiety groups were determined using SMARS. Across all prescreened subjects ( $N = 108$ ), math-anxiety ratings were in keeping with published norms (our sample: mean = 32.11, standard deviation [SD] = 15.39; Alexander and



**Figure 1.** Behavioral results: error bars indicate standard errors of the mean. Note that only HMAs showed a significant difference between tasks (more errors on the math task).

Martray 1989; mean = 31, SD = 16). To maximize group differences, upper and lower quintiles of the prescreening group (27 of the original 108 subjects were deemed unsuitable for scanning due to handedness, outlier responses on one of the other self-report measures, neurological abnormalities, or safety concerns) were selected to participate in the fMRI portion of the study: HMA mean = 49.56, SD = 6.98; LMA mean = 15.00, SD = 5.78. Of the 32 subjects thus scanned, 4 were removed from the data set; 2 were removed due to major scanner artifact, and 2 were removed because of excess motion. The remaining 28 subjects were divided into high (HMA: 8 females) and low (LMA: 7 females) math-anxious groups. Note that HMAs and LMAs did not differ in terms of either trait anxiety (Spielberger et al. 1970) ( $P = 0.5438$ ) or working memory capacity (Unsworth et al. 2005) ( $P = 0.9134$ ).

#### fMRI Task Procedure

Subjects performed 2 different tasks (math and word task) in blocked fashion. Two levels of difficulty were included for each task: hard and easy. Note, however, that the Group  $\times$  Task interaction did not obtain for easy problems ( $F < 1$ ) (for further details, see Supplementary Information), a result in keeping with previous work showing that HMAs' performance is primarily impacted on math problems with high working memory demands (Ashcraft and Krause 2007). Thus, brain-behavior analyses were limited to hard problems. Critically, before each block of trials, a cue was provided that indicated which type of task was about to follow (the cue did not identify task difficulty). Cues were either a yellow circle or a blue square. Which cue indicated which task was randomized across subjects. Cues predicted the corresponding task with 100% accuracy.

To increase their functional saliency, cues always preceded blocks of 4 trials each. For example, if a flashing square indicated math trials, this cue was succeeded by a block of 4 math trials. The 4 trials in a block were separated by a fixed interstimulus interval of 1500 ms. Each trial had a 5.5 s cut off. This cutoff was well above average task response times (see Supplementary Information). Cues were presented for 1500 ms. Fixation time between cue offset and trial-block onset was jittered between 2500 and 6500 ms. This was done to separate neural signals generated by the cues and signals generated by performing the actual tasks. Fixation time between trial-block offset and onset of the cue for the following block was 18 s to allow for resolution of the hemodynamic response between blocks. This rest period was used to model baseline activity (modeled for each group separately). Participants completed 32 blocks of each task type over the course of 8 functional runs, with 4 blocks of each task presented in each run.

#### Math Task

Subjects verified whether arithmetic problems had been correctly solved. All problems were of the form  $(a \times b) - c = d$ ; where  $a \neq b$ ,  $c > 0$ ,  $d > 0$ ; for hard math problems,  $5 \leq a \leq 9$ ,  $5 \leq b \leq 9$  ( $a \times b \geq 30$ ), and  $15 \leq c \leq 19$ ; for foil problems,  $d \pm 2$ . In addition, subtracting  $c$  from  $a \times b$  always involved a borrow operation. Subjects pressed a key with either their left or right index finger to indicate whether the problem had been solved correctly (which hand indicated which response was randomized across subjects; response randomization was independent of cue randomization).

#### Word Task

Subjects verified whether a word, if reversed, spelled an actual English word (all subjects were fluent English speakers). For half of the words, 2 internally adjacent letters were switched such that reversing the whole letter string would result in a nonword. For example, if subjects saw the string *meimrepxe*, reversing this string would generate *expermiemt*. Because the i and the m have been switched, this is not an English word, and subjects should respond "no." For hard word problems, strings were always 7 letters in length. Subjects pressed a key with either their left or right index finger to declare whether the string, when reversed, produced a real word or not. To avoid subject confusion, the hand that indicated "not correct" for the math problems also was used to indicate not correct for the word problems.

We chose this task because we were primarily concerned with creating a control task that was decidedly nonmathematical in nature but similar to the math task in terms of response and general task-set properties (both were two-alternative, forced-choice verification tasks). Crucially, the control task was designed to be as difficult as the hard math-task—from at least one objective source (behavioral data)—in the LMA group. We also ensured that performance did not significantly differ across the HMA and LMA groups on this task (see behavioral results).

After completion of all scans, subjects were verbally probed to see (1) if they actually knew which cue prompted which task: all subjects responded correctly to this question, and (2) if they had inferred the true focus of the study (math anxiety): none reported having done so.

#### fMRI Data Acquisition and Analysis

##### Acquisition and Preprocessing

MRI data were acquired using a 3-T Philips Achieva scanner with an 8-channel Philips Sense head coil. A  $T_2^*$ -weighted echo-planar imaging sequence was used to acquire functional images covering the whole brain (32 axial slices) with a repetition time of 2000 ms and an echo time of 25 ms (ascending acquisition; field of view [FOV]:  $240 \times 240 \times 127.5$  mm;  $80 \times 80 \times 32$  matrix; flip angle:  $80^\circ$ ). In-plane resolution was  $3 \times 3$  mm, and the slice thickness was 3.5 mm (0.5 mm skip). Signal from the orbital frontal cortex (OFC) and surrounding tissue was recovered using additional volume shimming with a box of  $60 \times 60 \times 60$  mm centered on the OFC area. This method utilizes multiple "pencil beam" acquisitions to compute shim values, using a pencil beam volume shimming algorithm provided by Philips. Whole-brain high-resolution anatomical images were acquired in the axial plane (300 slices; slice thickness: 1.2 mm,  $-0.6$  mm gap;  $x$ - $y$  dimensions:  $1.04 \times 1.04$ ; FOV:  $250 \times 250 \times 180$  mm,  $240 \times 240 \times 300$  matrix) with a standard Philips  $T_1$ -weighted SENSE-Ref sequence.

All preprocessing steps and whole-brain data analyses were conducted using BrainVoyager QX (version 1.10.4, Brain Innovation, The Netherlands). Functional images were first slice-time corrected and then motion corrected using sinc interpolation. A high-pass general linear model (GLM) (Fourier basis set) temporal filter removed fluctuations  $< 2$  cycles, which also removed linear temporal drift. Each functional run was then manually aligned to the subject's 3D anatomical image, both of which were then transformed into Talairach space. Resulting volumetric time-series files were then spatially smoothed with a 6 mm full-width at half-maximum Gaussian kernel.

Data were next submitted to a random effects GLM (Friston et al. 1994) with 6 main predictors of interest: math cue, word cue, hard and easy math task blocks, and hard and easy word task blocks. Seven predictors of no interest (motion parameters and errant button

presses) were included in the model. In each voxel and for each subject, parameter estimates (hereafter  $\beta$ s) for each subject and each condition were thus generated. All second-level analyses (see below) were conducted using these voxelwise  $\beta$ s.

### Second-Level Analyses

For all whole-brain analyses below, statistical maps were thresholded at  $P < 0.005$  and, subsequently, cluster level corrected for multiple comparisons using a Monte-Carlo simulation procedure (Forman et al. 1995) with a family-wise false positive rate  $\alpha = 0.05$ . With respect to region of interest (ROI) analyses, for each subject and predictor, ROI-level  $\beta$ s were determined by averaging  $\beta$ s from all voxels comprising the ROI volume in question (for that subject and that predictor). Once extracted, ROI  $\beta$ s were submitted for analysis in Matlab.

In light of recent debate (Kriegeskorte et al. 2009; Vul et al. 2009) regarding the reporting of correlational values (upon which some of our analyses rest), we believe we would be remiss if we did not mention that  $r$  values, like any other summary statistic, carry a certain degree of imprecision, which is exacerbated in cases involving relatively few degrees of freedom. Therefore, in all tables where we report correlation estimates expressed either in terms of SDs ( $r$  values) or arbitrary units ( $\beta$  values), we provide standard errors of that estimate as well (denoted in parentheses beside the actual estimate). Figures depicting fitted regression lines also contain 95% confidence interval ranges for these fitted estimates.

## Results

### Behavioral Results: Math Anxiety and Individual Performance Differences

Our primary behavioral measure of interest was task error rates (proportion wrong), which coincides with the fact that performance accuracy is what students are graded on in a majority of math performance situations (Note that behavioral results were similar for response times [see Supplementary Information]; importantly, there were no (speed-accuracy) trade-offs between response times and error rates [all  $\beta$ s  $\geq 0.374$ ]).

As mentioned above (also Fig. 1), HMAs produced significantly more errors than LMAs on the math task ( $t_{26} = 3.50$ ,  $P = 0.0017$ ), but the 2 groups did not differ on the difficulty-matched word task ( $t_{26} = -0.02$ ,  $P = 0.9923$ ). Furthermore, HMAs performed more poorly on the math relative to the word task ( $t_{13} = 3.80$ ,  $P = 0.0022$ ); LMAs did not ( $t_{13} = 0.61$ ,  $P = 0.5535$ ). (Group  $\times$  Task interaction:  $F_{1,26} = 16.15$ ,  $P = 0.0004$ ,  $\eta^2 = 0.383$ .)

Importantly, some HMAs showed a larger math deficit (math errors minus word errors) than others. Note, however, that a self-report measure of math anxiety (Alexander and Martray

1989) was not correlated with math deficits in the HMA group ( $P = 0.4634$ ).

### Analysis 1: Cue Activity–Math-Deficit Correlations

To determine why some HMAs showed larger math performance deficits than others, we began by relating math deficits (difference between math and word error rates) to neural activity evoked when faced with the prospect of doing math. We regressed behavioral math deficits on neural activity during math cue presentation (controlling for word cue activity). For HMAs, this math deficit was a distribution of positive values; for LMAs, it centered on zero. The LMA group served mainly as a control group in demonstrating that our effects were specific to HMAs, as LMAs had no math deficit to explain. Thus, we tested whether the observed correlation for HMAs was specific to that group—that is, whether the slope of predicted math deficits from cue activity depended on math-anxiety group.

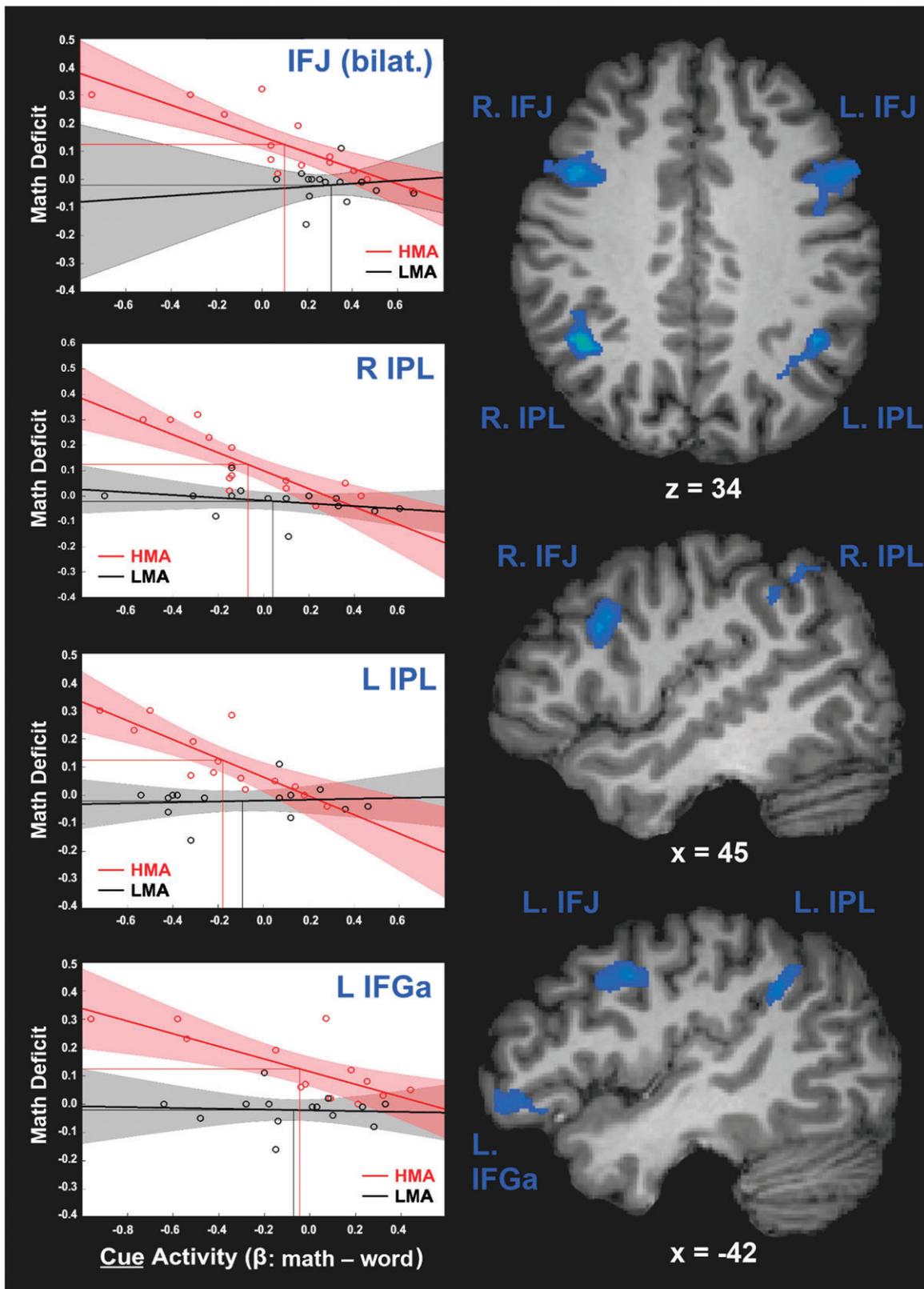
For HMAs, as math deficits decreased (i.e., less of a difference between math and word error rates), differences in cue activity (math–word) increased in several regions. These regions were bilateral inferior frontal junction (IFJ), bilateral inferior parietal lobe (IPL; this cluster spanned the junction between angular and supramarginal gyri), and left anterior inferior frontal gyrus (IFGa). No significant regions were found for LMAs. Table 1 (top) summarizes region details; regions and regression diagnostics are shown in Figure 2. Note that the relation between cue activity and math deficits remained highly significant ( $P$ s  $< 0.005$ ) even when controlling for ratings of math anxiety (SMARS). Thus, for HMAs, it is not necessarily the level of one's self-reported math anxiety per se that predicts one's math deficit; rather, it is one's ability to call upon frontoparietal regions before the math task has even begun—regions hypothesized to be involved in both cognitive control (Brass et al. 2005; Derrfuss et al. 2005, 2009) and regulating negative emotional responses (Ochsner et al. 2004; Bishop 2007). A significant Group  $\times$  Slope interaction obtained in all regions (all  $P$ s  $\leq 0.0330$ ): the relation between math deficits and frontoparietal cue activity was specific to HMAs.

Because math deficits were regressed on the difference between math cue and word cue activity ( $\beta$ s), it is important to determine whether math cue or word cue activity drove the observed effect in each region. Table 2 (“Correlation Splits” columns) shows HMA correlation results for each cue  $\beta$  separately (i.e., the correlation between raw subject  $\beta$ s and performance deficits) (LMAs were not considered as there

**Table 1**  
ROI details for Analyses 1 (top) and 2 (bottom)

Region	Talairach coordinates			Volume (mm <sup>3</sup> )	Correlations		Group $\times$ Slope
	x	y	z		HMAs	LMAs	
R. IFJ	44	13	31	2124	−0.762 (0.116), $P = 0.0015$	−0.151 (0.271), $P = 0.6064$	$P = 0.0192$
L. IFJ	−45	7	36	1308	−0.778 (0.109), $P = 0.0011$	0.168 (0.270), $P = 0.5667$	$P = 0.0034$
R. IPL	43	−44	37	951	−0.816 (0.093), $P = 0.0004$	−0.279 (0.256), $P = 0.3337$	$P = 0.0011$
L. IPL	−38	−48	33	740	−0.798 (0.101), $P = 0.0006$	0.087 (0.275), $P = 0.7679$	$P = 0.0006$
L. IFGa	−40	43	−4	942	−0.720 (0.133), $P = 0.0037$	−0.064 (0.276), $P = 0.8267$	$P = 0.0330$
R. Caud and NAc	9	14	2	1420	−0.882 (0.061), $P < 0.0001$	0.451 (0.221), $P = 0.1059$	$P < 0.0001$
L. Hipp	−23	−23	−5	800	−0.849 (0.077), $P = 0.0001$	0.189 (0.267), $P = 0.5186$	$P = 0.0005$

Note: For Analysis 1, cue activity (math > word) was correlated with math deficits (math > word error rates). For Analysis 2, task activity (math > word) was correlated with math deficits (math > word error rates). Note that all ROIs were localized for HMAs. The rightmost 3 columns reflect correlation details for each region. The first 2 of these columns report mean  $r$  values (i.e., averaged across all voxels in the ROI), corresponding standard errors (in parentheses), and  $P$  values for each group. The final column reports the  $P$  value associated with the interaction term testing for whether the observed correlation was in fact specific to the HMAs.



**Figure 2.** Depiction of regions and scatter plots from Analysis 1. No effects of hemisphere were found for IFJ regions; thus data are averaged across the 2 hemispheres in the scatter plot above. Shaded areas in the scatter plots represent 95% confident intervals (observed) for the fitted linear regression line. MC, math cue; WC, word cue. Y-axis: math deficits (higher number = higher math [relative to word] error rate).

**Table 2**

ROI verification results for Analyses 1 (top) and 2 (bottom)

Region	Correlation splits		HMA raw $\beta$ s		LMA raw $\beta$ s	
	Math $\beta$	Word $\beta$	Math $\beta$	Word $\beta$	Math $\beta$	Word $\beta$
R. IFJ	-0.726 (0.131), $P = 0.0033$	-0.051 (0.277), $P = 0.8626$	0.001 (0.113)	-0.127 (0.096)	0.152 (0.104)	-0.162 (0.112)
L. IFJ	-0.625 (0.169), $P = 0.0170$	0.117 (0.274), $P = 0.6896$	0.008 (0.103)	-0.068 (0.088)	0.130 (0.082)	-0.123 (0.105)
R. IPL	-0.729 (0.130), $P = 0.0031$	-0.170 (0.269), $P = 0.5601$	-0.086, (0.101)	-0.016 (0.075)	-0.150 (0.106)	-0.177 (0.098)
L. IPL	-0.696 (0.143), $P = 0.0057$	-0.103 (0.274), $P = 0.7259$	-0.029 (0.100)	0.153 (0.074)	0.012 (0.122)	0.102 (0.088)
L. IFGa	-0.032 (0.277), $P = 0.9129$	0.584 (0.183), $P = 0.0282$	-0.013 (0.106)	0.031 (0.123)	-0.060 (0.094)	0.012 (0.095)
R. Caud and NAc	-0.630 (0.167), $P = 0.0158$	0.116 (0.274), $P = 0.6935$	0.042 (0.079)	-0.006 (0.094)	0.230 (0.066)	0.135 (0.048)
L. Hipp	-0.723 (0.132), $P = 0.0035$	-0.063 (0.276), $P = 0.8302$	0.128 (0.100)	0.177 (0.070)	0.011 (0.089)	-0.009 (0.080)

Note: For Analysis 1, cue activity (math or word) was correlated with math deficits (math > word error rates). For Analysis 2, task activity (math or word) was correlated with math deficits (math > word error rates). Columns labeled Correlation Splits contain HMA correlation results for each task  $\beta$  separately (i.e., the correlation between raw, nonsubtracted, subject  $\beta$ s, and performance deficits). Cell values report mean  $r$  values (i.e., averaged across all voxels in the ROI), corresponding standard errors (in parentheses), and  $P$  values for each cue/task type. LMAs were not considered here as there was no correlation for LMAs in these regions. For Analysis 1, these data demonstrate that the correlations in IFJ and IPL regions were driven primarily by math-cue activity; by contrast, the correlation in left IFGa was driven primarily by word-cue activity. For Analysis 2, correlations in both right caudate/nucleus accumbens and left hippocampus were primarily driven by math-task activity. The rightmost 4 columns contain raw (nonsubtracted)  $\beta$ s (and standard errors) for both groups and conditions.

were no significant cue–performance relations identified for this group). The correlations in IFJ and IPL regions were driven primarily by math cue activity. The correlation in left IFGa was driven primarily by word cue activity. This latter result is not surprising given that this region is canonically associated with semantic language processing (Vigneau et al. 2006).

To help understand the above results better, we divided the HMA group into 2 subgroups using a median split based on the difference between math cue and word cue  $\beta$ s in each of the ROIs found in Analysis 1. (Note that this clearly constitutes a form of “double-dipping” [Kriegeskorte et al. 2009] because these regions were localized based on the relation between math deficits and the difference between math- and word-cue activity in HMAs. However, this section is meant merely as an additional way of thinking about the data rather than as a definitive analysis unto itself. For simplicity, IFJ and IPL splits were based on average ranking across hemispheres.) It is worth noting that mean activity for HMAs was at or near baseline in all regions (Table 2: HMA Raw  $\beta$ s: Math  $\beta$ s). This was because about half of HMAs showed activation differences above baseline and the remaining half somewhere below baseline. Relative to the lower half of HMAs, the upper half tended to show greater math cue activity (IFJ: upper half:  $M = 0.268$ , lower half:  $M = -0.259$ ,  $t_{12} = 3.01$ ,  $P = 0.0109$ ; IPL: upper half:  $M = 0.155$ , lower half:  $M = -0.269$ ,  $t_{12} = 2.63$ ,  $P = 0.0218$ ; LIFGa: upper half:  $M = 0.176$ , lower half:  $M = -0.201$ ,  $t_{12} = 1.97$ ,  $P = 0.0724$ ) but not word cue activity (IFJ: upper half:  $M = -0.157$ , lower half:  $M = -0.039$ ,  $t_{12} = -0.74$ ,  $P = 0.4758$ ; IPL: upper half:  $M = 0.069$ , lower half:  $M = 0.068$ ,  $t_{12} = 0.01$ ,  $P = 0.9906$ ; LIFGa: upper half:  $M = -0.051$ , lower half:  $M = 0.116$ ,  $t_{12} = -0.66$ ,  $P = 0.5194$ ). In terms of performance, using a median split based on the average rank across all 5 regions, the upper half of HMAs showed 17.3% (hard)math errors, while the lower half showed 32.1% errors ( $t_{12} = 2.83$ ,  $P = 0.0152$ ). The 2 subgroups did not differ with respect to (hard)word errors (upper half: 14.4%, lower half: 10.3%,  $t_{12} = 0.86$ ,  $P = 0.4091$ ). Thus, HMAs who activated this frontoparietal network more for the math cue (but not the word cue) also showed nearly complete elimination of their math deficits (2.9%, on average), whereas those who did not show this activation had much greater math deficits (21.8%, on average).

In sum, increased frontoparietal activity in response to the prospect of doing math predicted reduction in the magnitude of math deficits in a manner that also depended on whether

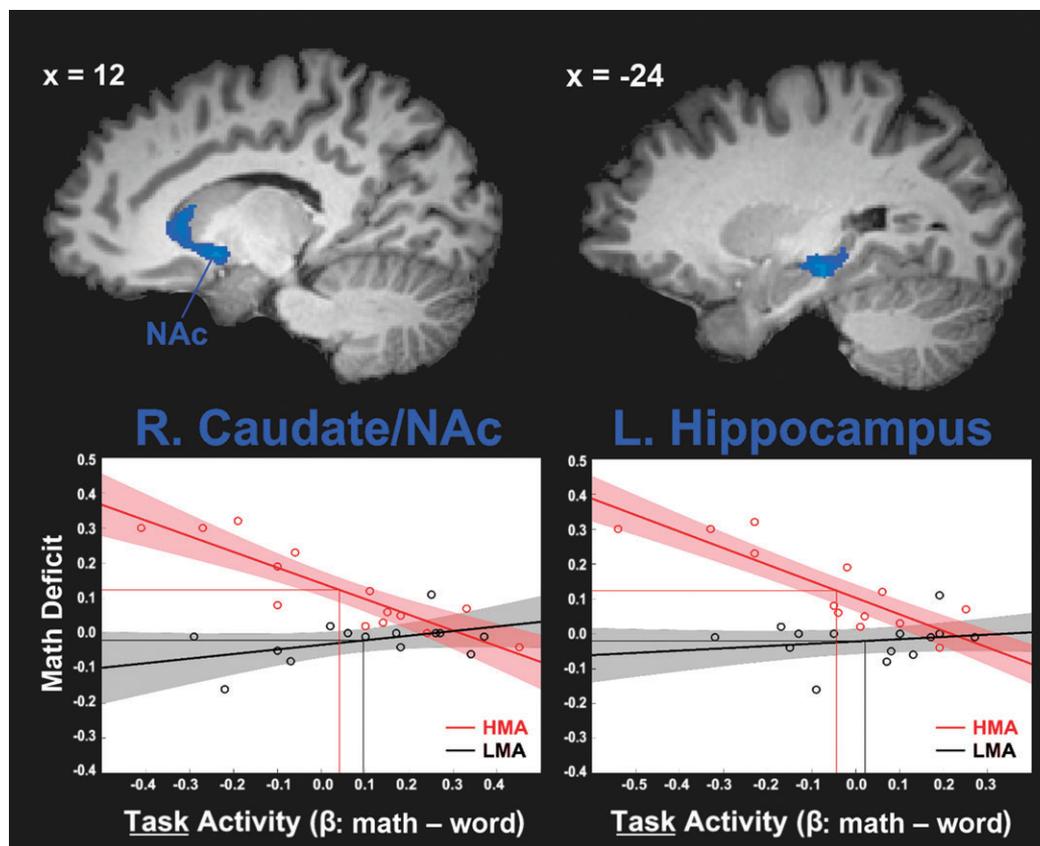
one was high in math anxiety. Presumably, then, there should be some neural region(s) whose activity during actual math performance directly mediates this relationship.

### Analysis 2: Task-Activity–Math-Deficit Correlations

We next investigated activity during math performance itself that might mediate (or account for) the relation between frontoparietal cue activity and HMAs’ math deficits. This analysis was conducted in the same manner as Analysis 1, with the exception that math deficits were regressed on the difference between math and word task (rather than cue) activity. Table 1 (bottom) summarizes region details; Figure 3 shows regions and regression diagnostics.

For HMAs, 2 regions showed a negative relation with math deficits: right dorsomedial caudate (overlapping with right nucleus accumbens) and left hippocampus. As the difference between math and word task activity increased (math–word), HMAs’ math deficit decreased. Significant Group  $\times$  Slope interactions indicated that this relation was specific to HMAs (Table 1, bottom). Furthermore, as seen in Table 2, the correlations in both regions were driven primarily by a negative relation between math task activity and math deficits: as math task activity increased, math deficits decreased. No significant regions were found for LMAs.

As with Analysis 1, to help understand these results better, we divided the HMA group into 2 subgroups, this time using a median split based on the difference between math task and word task  $\beta$ s in right caudate and left hippocampus. Relative to the lower half of HMAs, the upper half tended to show greater math-task activity (caudate: upper half:  $M = 0.228$ , lower half:  $M = -0.144$ ,  $t_{12} = 2.95$ ,  $P = 0.0121$ ; hippocampus: upper half:  $M = 0.275$ , lower half:  $M = -0.018$ ,  $t_{12} = 1.55$ ,  $P = 0.1480$ ) but not word task activity (caudate: upper half:  $M = -0.008$ , lower half:  $M = -0.004$ ,  $t_{12} = -0.04$ ,  $P = 0.9701$ ; hippocampus: upper half:  $M = 0.158$ , lower half:  $M = 0.196$ ,  $t_{12} = -0.26$ ,  $P = 0.7976$ ). In terms of performance, using a median split based on the average rank across the 2 regions, the upper half of HMAs showed 18.0% (hard)math errors, while the lower half showed 31.4% errors ( $t_{12} = 2.41$ ,  $P = 0.0327$ ). The 2 subgroups did not differ with respect to (hard)word errors (upper half: 13.4%, lower half: 10.9%,  $t_{12} = 0.61$ ,  $P = 0.5528$ ). Thus, HMAs who activated this network more for the math task (but not the word task) almost completely eliminated their math deficits (4.6%, on average),



**Figure 3.** Analysis 2 regions and scatter plots. Note that the right caudate region spans both the medial head of the caudate and nucleus accumbens (NAc). Shaded areas in the scatter plots represent 95% confident intervals (observed) for the fitted linear regression line. Y-axis: math-deficits (higher number = higher math [relative to word] error rate).

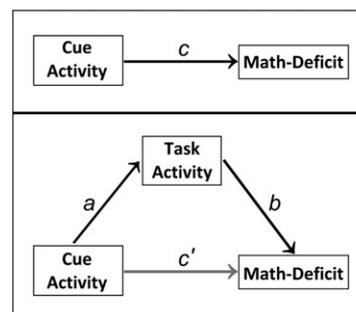
whereas those who did not show this activation difference had much greater math deficits (20.5%, on average).

### Analysis 3: Mediation Framework

In a mediation analysis, one asks whether the direct effect from an independent variable (IV) to a dependent variable (DV) can be accounted for by the indirect influence of a mediating variable (Fig. 4). Significance estimates for indirect effects were obtained via the bootstrapping method described in Preacher and Hayes (2008). We treated cue activity (math–word) as our IV (note that cue activity temporally preceded both task activity and behavioral performance), task activity as our mediating factors (math–word) and math-deficits as the DV we were interested in explaining. In sum, we asked whether task activity (in Analysis 2 regions) mediated the cue activity–math-deficit relation reported in Analysis 1.

To assess the criterion that the IV is related to the mediators, we first tested whether cue activity in the regions identified in Analysis 1 correlated with task-activity in the regions identified in Analysis 2. Right caudate task activity was positively correlated with cue activity in all 5 frontoparietal regions identified in Analysis 1 ( $P_s \leq 0.0058$ ). All effects were specific to HMAs ( $P_s \leq 0.0337$ ). Left hippocampus task activity was also positively correlated with cue activity in all 5 frontoparietal regions identified in Analysis 1 ( $P_s \leq 0.0037$ ). These correlations were specific to HMAs for all but left IFJ ( $P = 0.2468$ ; all other  $P_s \leq 0.0156$ ).

Both right caudate and left hippocampus were included as simultaneous mediators to examine their combined mediating



**Figure 4.** Mediation framework: we tested whether task activity in regions identified in Analysis 2 mediated the relationship  $c$  between math deficits and cue activity in regions identified in Analysis 1. In this framework, one asks whether there is a significant indirect effect of the mediator (quantified as the product of the unstandardized path coefficients,  $a$  and  $b$ , in the figure above) that accounts for some portion of the direct effect  $c$  originally observed between the independent (in this case, cue activity) and the dependent (in this case, math deficit) variables. When more than one mediator is considered at a time, the total mediating influence is the sum of the products  $ab_i$ , for  $i = 1 \dots n$  mediators. The remaining (unmediated) direct effect is denoted  $c'$ . Full mediation occurs when  $ab$  is significant but  $c'$  is not; partial mediation refers to when both  $ab$  and  $c'$  remain significant. Note that in this framework, the model is constrained by the assumption that  $c = ab + c'$ . In other words, unlike in a standard multiple regression analysis, we are explicitly asking what portion of the IV–DV (cue activity–math deficit) relationship can be accounted for by the proposed mediating variable (task activity).

effect. (Note that task activity in each region alone provided a significant mediating influence. However, because these 2 regions were highly correlated with one another in HMAs

[ $r = 0.919$ ], for simplicity, we treat them here as a single influence [for details, see Fig. 4]. Note also that hippocampus and dorsomedial caudate are highly interconnected and are thought to form a tightly coupled network that plays a role in flexible online processing [White 2009]. We treated each of the 5 cue regions (left and right IFJ, IPL, and left IFGa) as separate IVs. In addition, we constructed a model that assumed the net signal from all 5 regions served as a unified (averaged) signal. This was because, for HMAs, cue activity (math cue – word cue) was highly correlated between these regions (mean  $r = 0.809$ ; range: 0.745 to 0.898). In this way, 6 separate models were run: one for each of the 5 cue regions and one for the cue network average. The combined mediating effect of right caudate and left hippocampus was significant in all 6 models ( $P_s \leq 0.0206$ ) (Table 3). In sum, hippocampus and caudate/NAc task activity mediated the frontoparietal cue activity–math-deficit relation seen in Figure 2.

### Discussion

Our central aim was to identify neural areas—during both the anticipation and performance of math—that predict variation in the math deficits exhibited by HMAs individuals. In doing so, we reveal (1) neural evidence that the negative relation typically seen between math anxiety and math competence arises even before math performance begins, and (2) how some HMAs may overcome this math-specific deficit.

Math deficits were predicted by cue activity in a network of inferior frontoparietal regions (IFJ, IPL, left IFGa) and in a manner statistically specific to HMAs—a relation driven primarily by math-cue activity in the IFJ and IPL regions (Tables 1 and 2). One possibility is that the reduced math deficits exhibited by some HMAs are the result of these individuals ramping up cognitive control resources when anticipating math in a manner that allows them to change the way they approach performing the upcoming math task.

The bilateral IFJ regions in particular correspond to an area of the cortex associated with high-level cognitive control processes such as task- or set-shifting and inhibition of prepotent responses (Brass et al. 2005; Derrfuss et al. 2005, 2009). A prominent theory regarding the negative impact of anxiety on cognitive task performance (attentional control theory) (Eysenck et al. 2007) suggests that anxiety compromises performance via limiting the successful operation of attention shifting and inhibitory processes. For instance, anxious individuals, when in the context of emotion-inducing stimuli, tend to exhibit poorer control of saccades (Ansari

et al. 2008; Wieser et al. 2009), poorer task-switching ability during mental arithmetic performance (Derakshan et al. 2009) and poorer performance in an emotional Stroop paradigm (Reinholdt-Dunne et al. 2009). This evidence is also consistent with the suggestion that math anxiety involves a reduction in control-related working memory capacity (Hopko et al. 1998; Ashcraft and Krause 2007; Beilock 2008). Our results suggest that, in a math-anxiety-inducing context, some HMAs are able to overcome such attentional deficits by ramping up control resources before the math itself begins—a process which may allow them to reappraise their approach to the upcoming math task as well.

Consistent with this view, in a meta-analysis, Bishop (2007) identified a cluster of activations centered on bilateral IFJ associated with interpretation of potentially threat-related stimuli. Similarly, Ochsner et al. (2004) found that regulation of negative emotions via reappraisal was related to increased activity in bilateral DLPFC (note that in many studies cited, activations overlapping with the IFJ region reported here are sometimes labeled “DLPFC”). Overlap between activations seen in Ochsner et al. (2004) and the IFJ regions in the current work was observed in the Ochsner et al. (2004) condition where participants were explicitly instructed to reduce the interpreted negative emotional content of visual images. Thus, it may be that HMAs who most successfully reappraised their negative emotional response to the prospect of doing math are most successful at reducing math deficits. Importantly, according to this interpretation, such a relationship should not be seen for LMAs because they do not have a negative emotional response in anticipation of math that requires reinterpreting.

In addition, it is worth noting that cue activity was not related to math deficits in regions typically associated with anxiety responses (e.g., amygdala [LeDoux 2000], hypothalamus [Dedovic et al. 2009], insula [Domschke et al. 2010]). Moreover, task activity in regions associated with arithmetic calculation did not predict math deficits in HMAs either (e.g., left IPS [Simon et al. 2002]). Thus, our data are most consistent with the notion that HMAs’ math deficits are determined primarily by how well they respond to and perhaps reinterpret their anxiety response rather than by the magnitude of those anxiety responses or their math skills per se.

Cue activity was positively correlated with task activity in 2 subcortical regions: right caudate nucleus and left hippocampus—again, in a manner specific to HMAs. Task activity in these regions was in turn correlated with performance, such that HMAs who showed relatively greater math- than word-task activity showed the smallest math deficits. In

**Table 3**  
Mediation analysis for HMAs

Independent variable (cue activity)	Combined mediators (task activity) L. Hipp and R. Caud/NAc		
	Original IV-DV effect ( <i>c</i> )	Mediation effect ( <i>ab</i> )	Unmediated effect ( <i>c'</i> )
R. IFJ	–0.246 (0.060), $P = 0.0015$	–0.152 (0.061), $P = 0.0129$	–0.094 (0.064), $P = 0.1771$
L. IFJ	–0.258 (0.060), $P = 0.0011$	–0.156 (0.058), $P = 0.0071$	–0.102 (0.060), $P = 0.1219$
R. IPL	–0.355 (0.073), $P = 0.0004$	–0.210 (0.077), $P = 0.0066$	–0.145 (0.088), $P = 0.1307$
L. IPL	–0.334 (0.073), $P = 0.0006$	–0.202 (0.073), $P = 0.0056$	–0.132 (0.080), $P = 0.1283$
L. IFGa	–0.223 (0.062), $P = 0.0037$	–0.139 (0.060), $P = 0.0206$	–0.084 (0.059), $P = 0.1839$
Network average	–0.318 (0.064), $P = 0.0003$	–0.182 (0.068), $P = 0.0071$	–0.154 (0.079), $P = 0.0802$

Note: The 6 models considered are listed in rows under Region. Original IV-DV effect (denoted *c* in Fig. 4) refers to the original cue–performance relationship to be explained. Total mediation effect (product of *a* and *b* in Fig. 4) refers to the IV-DV effect indirectly explained by the combined influence of mediator (task activity in both left hippocampus and right caudate/NAc). (Individual region contributions for left hippocampus and right caudate/NAc can be found in Supplementary Information.) Nonmediated IV-DV effect (denoted *c'* in Fig. 4) refers to the remaining effect of the IV on the DV that cannot be explained by the mediators. Cell values: linear regression estimate, (standard error),  $P$  value.

addition, this task activity fully mediated the relation between cue activity (in regions noted above) and math deficits in HMAs. Dorsomedial caudate and the hippocampus (especially the fimbria-fornix substructure) are highly interconnected regions and have been shown to cooperate in flexible stimulus-response learning in rats (White 2009). Interestingly, right caudate and left hippocampus have been found to be functionally interconnected in humans in the context of active episodic and semantic memory retrieval (Burianova and Grady 2007)—which is highly consistent with the strong degree of functional connectivity found between HMA right caudate and left hippocampus in our data. Left midposterior hippocampus in particular is thought to be central to maintaining information in one's episodic working memory buffer (Rudner et al. 2007; Berlingeri et al. 2008). Together, these regions are thought to play a central role in integrating higher level cognitive control of goal-driven actions (i.e., through selection of appropriate action schemas) with motivational and reward context (Grahn et al. 2008).

Anatomically the caudate head receives primarily glutamatergic inputs from prefrontal areas such as DLPFC and anterior cingulate cortex, as well as dopaminergic inputs arising from nearby nucleus accumbens and ventral midbrain regions (Utter and Basso 2008). Dopamine levels in dorsal caudate have also been shown to correlate with delay activity (i.e., while holding information in mind) in left IFJ during a Sternberg delayed-recognition working-memory task (Landau et al. 2009). One interpretation of the mediating role observed for caudate in the current data set is that HMAs who show the smallest math deficits do so because they are able to dynamically reorganize their approach to doing math. If HMAs' default response is to avoid math or just wait for it to be over, a more approach-oriented response is likely needed to successfully engage in the actual cognitive requirements of math performance (Markman et al. 2006). Consistent with this interpretation, the caudate region we identified also overlaps with nucleus accumbens (Fig. 3). Nucleus accumbens is believed to be central for motivating behavior (both appetitive and aversive) and regulating effortful functioning (Salamone 1994; Nicola et al. 2005; Salamone et al. 2007).

To summarize, we demonstrate that the mechanisms associated with the reduction—and even elimination—of math-specific performance deficits in HMAs are initiated before actual math processing occurs. However, it is not variation in HMAs' math anxiety per se that best predicts the extent of their math-specific deficits. Rather, our data indicate that the extent of HMAs' math deficits is associated with the ability to ramp up cognitive control resources in response to the prospect of doing math, which leads to a reorganization of task priorities, due at least in part to motivational factors. To our knowledge, this work serves as the first evidence from cognitive neuroscience in support of the idea that education interventions which emphasize the control of negative emotional responses to math stimuli may reveal a population of potentially numerically competent individuals (see McCandliss 2010, in support of an educational neuroscience approach more generally). In particular, the fact that PFC regions typically associated with cognitive control and working memory processes (Kane and Engle 2002; Brass et al. 2005) were found to be related to performance during the cue but not the actual task is highly consistent with the process model of emotion regulation proposed by Gross (1998, 2002). In this

model, emotional control processes that act early on the arousal of negative affective responses (e.g., reappraisal) are more effective at mitigating these responses and limiting concomitant performance decrements than explicit suppression of these responses later in the affective process (e.g., during online performance). Interestingly, recent evidence has shown that a similar approach highlighting the reappraisal of negative emotional reactions has proven effective, for example, in allaying the negative impact on math performance due to fear of confirming negative stereotypes about one's academic abilities (i.e., stereotype threat; Johns et al. 2008).

The current findings therefore suggest that best educational practices for enhancing math competency in HMAs is not to generate costly math courses specifically for the HMAs (Gresham 2007) nor is the best method likely to be one that focuses solely on eliminating one's initial anxiety response (for a review of these and other approaches, see especially Hembree 1990). Instead, classroom practices that help students learn how to marshal cognitive control resources and effectively check one's math-related anxiety response once it occurs—but before it has a chance to reduce actual math performance—will likely be the most successful avenue for reducing anxiety-related math deficits.

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## Supplementary Material

Supplementary material can be found at: <http://www.cercor.oxfordjournals.org/>

## Notes

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