The Developing Math Brain: An fNIRS Study

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Introduction

For decades, researchers have studied the origins of language and its relation to future reading ability. Not only has this research provided a developmental map that allows us to have a better understanding of the normal development of language and reading, but it has also contributed to better instruction methods in language and literacy, as well as presents us with early identification of children at risk for reading impairments. Given that our ability to count is equally as important as knowing how to read in terms of academic achievement (Claessens, 2009; Duncan, 2007; Ginsburg, 2008), it comes as a surprise that there is much less parallel research in the area of mathematics.

While the field of language and literacy acquisition now offers a rich body of evidence-based methods for identifying preschoolers at risk for linguistic delays, the numeracy field is in the relatively early stages of understanding the process of number representation (Hyde & Spelke, 2011). Recent evidence suggests that children's knowledge of division might be a critical component of emergent numerical cognition and a better predictor of later mathematical achievement as compared to children's ability to add, subtract, or multiply (Siegler et al., 2012). In young children the ability to divide can be demonstrated through resource sharing activities (Larsen, 1974; Olson, 2008). Thus, the present study focused on exploring the cognitive and brain mechanisms that support individuals' ability for division in the context of social resource-sharing activity.

Numerical Cognition.

Research in the field of numerical cognition has suggested our ability to think and reason about number emerges from two core systems (Feigenson et al., 2004; Pica et al., 2004). The first core system, which has been referred to as the "numerical magnitude" system, represents the understanding of large, approximate numerical magnitudes. For example, 6-month old infants are able to discriminate between numerically familiar and numerically novel test arrays (Xu & Spelke, 2000). The second core system, which has been referred to as the "parallel individuation" system, represents the ability to keep track of precise small numbers of individual objects and represents information about each object's continuous quantitative properties. For example, 10-12-month olds were able to discriminate between a larger and smaller quantity of crackers, but only for ratios of 1 vs. 2, and 2 vs. 3 (Feigenson et al., 2002). Thus, unlike the numerical magnitude system in which the child keeps track of an overall amount, in the parallel individuation system children keep track of narrower, better-defined quantities. These two systems are believed to account for our foundations of numerical concepts.

A better understanding of these foundational concepts has allowed researchers to produce predictive theories of numerical cognition. There are currently numerous theories that utilize these foundational concepts as building blocks, but emerging evidence is consistent with the majority of views, which believes each system engages different brain regions in qualitatively different ways (Hyde & Spelke, 2012).

One commonly used numerical cognition model is the 'triple-code' model, which builds upon these foundational concepts, as well as makes specific predictions of neuroanatomical correlates (Dehaene & Cohen, 1995, 1997; Dehaene et al., 2003). This model is based primarily off of adult data and follows three criteria: first, the ability to attend numerosity and manipulate elementary computation internally is present in animals (Hauser, Carey, & Hauser, 2000). Second, prior to any schooling or development in language skills, humans demonstrate an understanding of elementary number processing (Xu & Spelke, 2000). Finally, number processing can be seen in a neural circuitry reproducible and identifiable in different subjects across methods (Dehaene et al., 1998). This hypothesis is largely lateralized in the left hemisphere, providing little evidence on the entire brain region.

An emerging theory has been presented by Daniel Hyde and Elizabeth Spelke (2012), which builds upon foundational concepts based on a small (parallel individuation) number system and a large (numerical magnitude) number system. Such research has proposed engagements in the right TPJ and left intraparietal regions for small number changes, which are indicative of change detection and related to numerical symbols automatically evoked. On the other hand, it has proposed engagements in the right parietal and occipital regions for large number changes, which are indicative of an approximate number representation.

Mathematics in the Brain.

The abundance of neuroimaging research on language acquisition has suggested that differences in children's brain activation can precede and predict future achievements in reading acquisition (Raschle et al., 2012; Hoeft et al., 2007). It is thus possible, that children's neural representations of early mathematical ability can help better explain the nature of how children's early number sense develops into an elaborate mathematical ability, as well as provide additional tools for early identification and target treatment of children at risk for math-related learning impairments.

Neuroimaging research on numerosity has suggested that parietal regions, especially the intraparietal sulcus (IPS) and angular gyrus, the occipito-temporal areas, and the frontal lobes are active during tasks of numerical cognition (Arsalidou & Taylor, 2010; Dehaene et al., 2004; Grabner et al., 2007). Damage to parietal regions has been associated with deficits in visual-spatial and numerical fact retrieval, and children with dyscalculia typically show reduced activation in these regions.

Division.

As research in the field of numerical cognition works to identify the core cognitive correlates, the field is also working to identify predictors of later mathematical achievement in schooling. Many studies have discussed the importance of addition, subtraction, or division skills leading to future achievement, however there is disagreement as to what specific skills are critical for achieving mathematical competence and which leads to future achievement (Price, 2013; Mulligan, 1997). Until recently, most of the research in this area had focused on the knowledge and development of whole numbers with little information on the development of division and fractions (Geary, 2006).

Emerging hypotheses discuss the value of fractions as a better predictor of later mathematical achievement as compared to children's ability to add, subtract, and multiply. In 2008 the National Mathematics Advisory Panel reported proficiency in fractions appeared to be the most important foundational skill for children and at the present time, seems severely underdeveloped. A recent study investigated this hypothesis by analyzing large, nationally representative datasets from the United States and the United Kingdom (Siegler et al, 2012). Findings showed that even after controlling for mathematical knowledge, IQ, working memory, family education and family income, students' early knowledge of fractions and whole number division, predicted high school mathematical achievement.

Despite the fact that recent research has provided evidence for fractions and division to be a foundational skill to mathematical achievement, the field is still unclear on certain division aspects. From the Siegler et al. study and other research in this area, what remains uncertain is how division skills are developed, what some possible neural correlates of division are, and why it may be important to mathematical achievement. This may be because division is a typically difficult task to test from a developmental perspective since division instruction usually begins around grade 3 in the United States (Common Core Citation). If this delay in training is due to an idea that younger children are unable to understand concepts of division, there is evidence suggesting otherwise.

Social Division.

Although formal division instruction begins relatively late into the school years, researchers have argued that the ability to divide resources is foundational to human social functioning (Sugiyama, Tooby, & Cosmides, 2002). The necessity to share food, toys and other items surrounds us from early life. Importantly, such social division tasks use items rather than numbers, thus combining both aspects of numerical magnitude and parallel individuation of numerical cognition that are thought to underlie the human number sense as suggested by theories of numerical cognition.

In studies of fairness in moral reasoning, we see that very young children can allocate toys and food equally in sharing tasks (Larsen, 1974; Olson, 2008), presenting the ability to divide items by 3 years of age. In another study (McCrink, 2009), children 4 and 5 years of age played a “giving game” and were asked to determine which of two puppets were nicer depending on the amount of chips they shared with the child. These chips were of monetary value to the child, and in trials that included each puppet giving absolutely equal amounts, such as three chips, 5 year olds were able to determine that the puppet giving proportionally more chips was nicer. This notion demonstrated an understanding of fractions and proportions. Hence, it is of particular interest whether this ability to be “fair” is an early indicator of children’s mathematical division skills.

Current study.

The goal of the present study is to explore whether social division and numerical division tasks tap into similar cognitive capacities, as measured through brain activity and a relation in task performance. The study aimed to shed light on the cognitive and neural mechanisms that support the division ability across symbolic and non-symbolic domains of numerical cognition and to pave way to neurodevelopmental research on early mental mechanisms that support the emergence of mathematical ability.

Adult participants completed tasks of social or non-symbolic division, as modeled upon prior measures of a social resource allocation task for young children (McCrink et al, 2009), as well as symbolic division. Based upon theories of the number sense, prior neuroimaging evidence, and research emphasizing division, we hypothesize symbolic operations for division is likely to engage the left and right intraparietal regions, but especially the left IPS (Dehaene et al., 2003). We hypothesize non-symbolic division is likely to engage the right TPJ region and left intraparietal region. Importantly, we predict that there will be overlapping patterns of activation between the symbolic and the non-symbolic tasks of division and that participant's performance on the two tasks will correlate, suggesting a common core cognitive for the two abilities. If our hypothesis is true, then such social division tasks may be further developed for use with pre-division instructed children to study the emergence of numerical abilities that are foundational to mathematics.

Method

Participants

Twenty-eight typically developing adults participated in the study (10 males and 18 females; mean age=249.64 months; SD= 18.82; range= 218-281 months). Participants were recruited and tested at the University of Michigan. The study was approved by the IRB.

Participants either received a monetary compensation or course-work credit. Due to technical imaging data recording errors for 3 participants, and data saving errors for 1 participant, imaging data is only available for 24 participants.

Behavioral Tasks

Background Questionnaire. Participants completed a set of questions (see Appendix) regarding their handedness and family information, basic developmental and educational history, and presence of any learning disabilities.

Verbal Intelligence. Participant's completed a standardized vocabulary subtest of the Kaufman Brief Intelligence Test, Second Edition (KBIT-2; 60 items; for more detail on test scoring and reliability see Kaufman & Kaufman, 2004). Participants heard a word or phrase and their task was to select one out of six pictures that corresponds best to the word or phrase.

Nonverbal Intelligence. Participant's completed a standardized nonverbal subtest of the Kaufman Brief Intelligence Test, Second Edition (KBIT-2; 46 items, Kaufman & Kaufman, 2004). Participants saw a stimulus picture and their task was to select one of five pictures that best fit with the stimulus picture.

Executive Functioning. Participants' executive functioning was measured with the standardized Head-Toes-Knees-Shoulders task (HTKS; 30 items, Ponitz, et al. 2008). Participants were asked to play a game in which they must do the opposite of what the experimenter's directions say varying from touching your head, toes, knees, or shoulders. While the task has been originally developed for children, the experimental conditions increase in their complexity and do allow room for error even in older children and adult participants.

Mathematical Ability. Participants' numerical development was measured with the standardized Woodcock-Johnson III Subtest, Math Calculation Skills (W-J III; 45 items, McGrew, K. S., Dailey, D. E. H., & Schrank, F. A., 2007). Participants were asked to answer questions on a worksheet to the best of their ability that included addition, subtraction, multiplication, division, and combinations of these basic operations, as well as some geometric, trigonometric, logarithmic, and calculus operations. See Table 2 for summary of all Behavioral Measures.

Functional Near Infrared Spectroscopy.

fNIRS. We used functional Near Infrared Spectroscopy (fNIRS) by TechEN to measure participants' brain activation. fNIRS is a relatively new technology for the study of human brain function. There were three reasons for choosing fNIRS brain imaging: first, fNIRS can measure brain oxygenation in frontal, temporal and occipital regions of interest; second, fNIRS allows for mathematical testing in an ecologically valid setting (ex: sitting in front of a computer screen as is common among students – rather then being confined to an fMRI tube); third, fNIRS is child friendly and will allow for the extension of this experimental protocol towards younger populations, in hopes of mapping a developmental trajectory of math acquisition from childhood to adulthood.

Experimental stimuli were presented using E-Prime 2 (Psychology Software Tools, Inc.) on a 23-inch Philips 230E Wide LCD screen connected to a Dell Optiplex 780 desktop computer. For each participant we took pictures of the cap placement at the end of the brain imaging session. The study used a TechEN-CW6 system with 690 nm and 830 nm wavelengths The OptSeq software (OptSeq2; Dale, 1999) was used to order the experimental and the jitter (fixation) trials.

Brain Imaging Setup.

Prior neuroimaging studies on numerical reasoning suggest superior parietal lobules (Arsalidou, 2010), inferior parietal lobule (Arsalidou, 2010; Hyde, 2010), DLPFC (Grabner, 2013), IPS (Cantlon, 2006; Dehaene, 2004, Lyons, 2013, Price, 2013), as well as the temporoparietal junction (TPJ) (Saxe, 2009) play a role in this ability. Thus, our probeset was designed to measure brain signal from those regions. Specifically, the probe configuration thus covered bilateral frontal, temporal, parietal and occipital regions of interest listed above. The caps were placed on the participants' head using 10-20 international system (Jurcak, Tsuzuki, & Dan, 2007), anchoring on Fp, P0, P3, P4, F7, and F8 coordinates for each participant and using caps that best fit the participants' head size. There were a total of 34 data channels (See Table 1). 12 channels using 1 emitter and 6 detectors on the left and right hemispheres, anchored at F7/F8 locations, covered the bilateral frontal lobe. These probes covered regions that include the IFG, the MFG, and the SFG. 18 channels using 4 emitters and 5 detectors on the left and right hemispheres, anchored at P3/P4 locations, covered the parietal regions. These probes covered regions that include the SFG, the IFG (including the IPS), the SMG, the MTG (including the TPJ), as well as the postcentral gyrus. The occipital region was covered by 4 channels using 1 emitter and 2 detectors on the left and right hemispheres, with an anchor point in the middle at PO. These channels covered the superior occipital regions. We used the Atlas Viewer Gui software to design the optode configuration, and EASYCAP (Svojanovsky, 2007) caps with TechEN-designed grommets imbedded into the cap to secure the optodes (see Fig.1).

Neuroimaging Tasks

Participants completed one non-symbolic and one symbolic mathematical task. The participants completed the Social Division task first and then were presented with the Numerical Equations.

Non-Symbolic Task.

Social Division. This task measured social division and children's sensitivity to ratios and was modeled after an experiment by McCrink et. al (2010). Participants were shown a partitioned screen with two animals. Each side of the screen varied between 1-9 pieces of candy. Participants then saw different amounts of candy moving down the screen towards them simultaneously from both characters. Using a button-pressing experimental set-up, participants were asked to decide which character is nicer or a better sharer. They indicated their responses by pressing the appropriate button to the appropriate side of the screen. There were three levels of difficulty in this task. Participants either saw a baseline trial, absolute trial, or a conflict trial (See Fig. 2).

> ***Baseline***. In the baseline trial, the character that gave the larger amount of candy was a better sharer. This meant the character gave the participant more of their portion. This condition is considered the easiest since the better sharer is giving the participant more candies.
>
> ***Absolute***. In the absolute trial, both characters are giving the same amount of candy to the participant, however one character starts with less candies. This meant, although both characters are giving the same amount, one character is giving more of their portion. The character that starts with fewer candies in this case is the better sharer. This condition is considered to be somewhat difficult since both characters are giving the same amount of candies.
>
> ***Conflict***. In the conflict trial, the character that gives the smaller amount of candy was a better sharer. This meant the character that gives fewer candies is giving more of their portion to the participant, although the other character is giving more candies. This

condition is considered to be the most difficult since the character giving more candies is not "as nice" as the character giving less.

This was an event-related design experiment with an average of 21 trials per condition (the design had 26 baseline trials, 20 absolute trials and 18 conflict trials to preclude participants from developing additional strategies for solving the task). Each trial lasted 3500 ms and there were 39 jitter (fixation) trials ranging from 1000-6000 milliseconds.

Symbolic Task.

Numerical Equations. This task measured participants' accuracy during numerical estimations of addition, subtraction, and division (see Fig. 3). During each trial, participants saw an equation (e.g., 8+4, 3-1, or 6 ÷ 3) with one possible answer on the left side of the screen, and another possible answer on the right side of the screen. The participants were asked to respond as quickly and as accurately as possible which of the two solutions was correct. For each condition, the design included two levels of difficulty. Easier equation trials involved adding, subtracting, or dividing by the number 1 (54 trials). More difficult trials involved adding, subtracting, or diving by any number other than 1 (54 trials). This was an event-related design with 36 trials per condition, each trial lasting 3000 ms, 46 jitter (fixation) trials ranging from 1000-4000 ms.

Procedure.

Participants first completed consent forms and a learning background questionnaire. The participants then underwent head measurement and the fNIRS cap placement procedure. Participants received instructions for each experimental task immediately prior to each experiment and practiced the task with stimuli that differed from the experimental stimuli. Participants completed the two experimental tasks. The order of the tasks remained the same across participants. Following brain imaging procedure, participants completed standardized assessments of verbal and nonverbal intelligence, executive functioning, and mathematical ability.

fNIRS Data Processing and Analysis.

Data processing was completed using Homer2, a MATLAB-based software (Huppert, Diamond, Franceschini, & Boas, 2009), along with several customized scripts. We preformed the following preprocessing steps in the following order: optical density change data conversion, data examination for all channels, motion artifact detection and correction, filtering, concentration change data conversion and general linear model based (GLM) regression. First, the raw time course data was converted into units of optical density change (ΔOD). Then the ΔOD data went through two quality control steps: participants who did not complete the entire tasks or had missing data (e.g. due to system error) were excluded from analysis. We then used the Prune Channels function in Homer2 to examine the signal to noise ratio in the ΔOD data, participants with less than 50% of channels passing the threshold in the 690 nm wavelengths were excluded. Next, we used the Motion Artifacts by Channel function in Homer2 to identity the motion artifacts in ΔOD time series. Motion artifacts were defined by identifying signals above or below a relative threshold of 10 standard deviations from the mean, or an absolute amplitude threshold of 0.5 within a time period of 0.5 seconds. We excluded trials with associated data identified as motion artifacts. Of the twenty-eight participants that participated in this experiment, twenty-four had usable data, and twenty-four passed these threshold criteria and were retained for further analysis. Finally, a lowpass filter with cutoff frequency at 0.8 Hz was applied to the ΔOD data and the hemoglobin concentration change data was calculated using the modified Beer-Lambert law, which yielded HbO (oxygenated hemoglobin), HbR (deoxygenated hemoglobin) and HbT (total hemoglobin) concentration change values.

Analyses were conducted using solely HbO data because previous fNIRS studies suggest HbO data is more reliable than HbR and HbT data (Hoshi, 2007). The data were analyzed using a GLM base regression that included the social division task: baseline, absolute, and conflict conditions, the equation task: addition, subtraction, and division conditions, and the rest (jittered fixation period) conditions as factors. Regressions for the following contrasts were conducted: baseline > rest, absolute > rest, conflict > rest, absolute > baseline, conflict > baseline, conflict > absolute, addition > rest, subtraction > rest, division > rest, subtraction > addition, division > addition, and division > subtraction. GLM regression analyses provided beta values for all such contrasts (see Tables 5 and 6).

For each within-task comparison, the statistical analyses were evaluated using the False Discovery Rate (FDR) correction at a threshold of $p<.05$. The FDR correction was carried out by first ordering the unadjusted p-values across channels for each analysis that channel undertook; $p_1 \leq p_2 \leq \ldots \leq p_m$, next we adjusted the threshold δ ($\delta = 0.05$) as $(j/m) \times \delta$ for each p-value, and declared the tests as significant if $p_j \leq (j/m) \times \delta$ (for more details on this method see Benjamini & Hochberg, 1995). Channels close together were hypothesized to be covering similar areas, and therefore were averaged in order to get an overall value of that area.

Results

Behavioral Results

See Table 3 for demographics and group performances on all tasks, including behavioral and imaging samples. The accuracy variable of the two imaging tasks presented ceiling effects, so reaction time was used in all behavioral measures. Participants performed significantly faster on the easier tasks in the non-symbolic imaging task (See Graph 1), however participants had a larger reaction time for subtraction than division in the symbolic imaging task (See Graph 2).

Overall, adults performed faster on the symbolic imaging task than on the innovative non-symbolic imaging task (Graph 3).

A repeated measures ANOVA with a Greenhouse-Geisser correction determined that mean reaction time for the social division task differed statistically significantly between conditions ($F(1.957, 48.935) = 8.105$, $p = .001$). Post hoc tests using the Bonferroni correction revealed that reaction time from the Baseline condition to the Absolute condition was not statistically significant ($p = .591$), reaction time from the Baseline condition to the Conflict condition was statistically significant ($p = .002$), and reaction time from the Absolute condition to the Conflict condition was also statistically significant ($p = .045$).

A repeated measures ANOVA with a Greenhouse-Geisser correction determined that mean reaction time for the equation task differed statistically significantly between conditions ($F(1.950, 48.747) = 40.554$, $p < .0001$). Post hoc tests using the Bonferroni correction revealed that reaction time from the Addition condition to the Subtraction condition was statistically significant ($p < .001$), reaction time from the Addition condition to the Division condition was statistically significant ($p < .001$), and reaction time from the Subtraction condition to the Division condition was also statistically significant ($p < .001$).

In order to examine the association between the imaging tasks and participants mathematical ability, a listwise bivariate correlation was performed (see Table 4). The correlation revealed a significant relation between the conflict trial of the social division task and the KBIT Verbal Knowledge task ($r= -.590$, $n= 18$, $p<.01$). There was also a relation between the division trial of the symbolic division task and the HTKS task ($r= -.418$, $n=22$, $p<.05$). We saw a trend in association between the conflict task and the three conditions of the equations task; the relation between conflict reaction time and addition reaction time($r= .145$, $n= 23$, $p=$

.489), the relation between conflict reaction time and subtraction reaction time (r= .252, n= 23, p= .225), and the relation between conflict and reaction time and division reaction time (r= .292, n= 23, p= .156).

We saw strong relations between the conflict condition of the non-symbolic division task and the three conditions of the symbolic division task, addition reaction time and conflict reaction time (r=.129, n=26, p=), subtraction reaction time and conflict reaction time (r=.237, n=26, p=), and division reaction time and conflict reaction time (r=.281, n=26, p=).

fNIRS Analyses by Regions of Interest.

The critical question of the study was whether a novel social division task taps into similar brain regions as typically measured by numerical division. In order to directly assess brain activation in the Conflict condition of our Social Division task relative to the Division condition of our Symbolic Numerical task, we compared participants' brain activation during each condition.

Frontal Lobe: In both the non-symbolic division task and the symbolic division task, the two experimental, or most difficult conditions (Conflict and Division) demonstrated greater activation in the Left MFG (Ch 1, 6), the Left SFG (Ch 2, 3), and the Left IFG (Ch 4, 5). The right frontal lobe did not show much activation during the non-symbolic division task, however drew the most activation for the addition condition in the symbolic division task in the Right MFG (Ch 34, 39), the Right SFG (Ch 33, 32), and the Right IFG (Ch 31, 30). See Graphs 1 and 2.

Parietal Lobe: The non-symbolic division task showed greater activation in all fourteen left and right parietal channels (CH 7-13, 22-28) in contrast to the symbolic division task, possibly because the symbolic division task was rather simple for our age group. However, we saw a positive activation draw from the Left IPL (CH 8, 10, 11, 12, 13) and the Left SPL (CH 14, 15) in the symbolic division task. See Graphs 3 and 4.

Occipital Lobe: The occipital lobe was used as a control to determine that our non-symbolic division task was drawing more activation in the visuo-spatial region of the brain when compared to the symbolic division task. The non-symbolic division task drew activation for the experimental tasks when compared to control (Ch 14-17, 18-21). The symbolic division task drew actvation for the control task when compared to the experimental tasks (Ch 14-17, 18-21). See Graphs 5 and 6.

Discussion

The present study examined whether social division and numerical division tasks tapped intro similar cognitive capacities, and aimed to shed light on the cognitive and neural mechanisms of division ability. First, we hypothesize symbolic operations for division is likely to engage the left and right intraparietal regions, but especially the left IPS. Then, we hypothesize non-symbolic division is likely to engage the right TPJ region and left intraparietal region. Finally, we predicted that there will be overlapping patterns of activation between the symbolic and the non-symbolic tasks of division and that participant's performance on the two tasks will correlate, suggesting a common core cognitive process for the two abilities.

Using an innovative social division task composed of baseline, absolute, and conflict conditions, we found that the accuracy of this task presented ceiling effects, and reaction time performance on each condition significantly differed from the other. Additionally, the two hardest conditions in this task (absolute and conflict) showed the largest amount of percent signal change in activation in the Left IPL. This suggests that although this was an easy task for adult participants, the area of the brain we hypothesize is responsible for numerical relations and proximity was recruited.

With a simple symbolic numerical equations task composed of addition, subtraction, and division conditions, we found that the accuracy of this task presented ceiling effects, and reaction time performance on each condition significantly differed from the other. Although the two hardest conditions in this task (subtraction and division) did not show the largest amount of percent signal change, possible due to the fact that these were too simple for adults, we still saw a particular pull toward our regions of interest for mathematical development: the left frontal lobe, as well as the left IPL.

By comparing all tasks participants completed, we were able to discuss possible similarities. We saw overlapping patterns in both the left frontal, and left parietal lobes for the symbolic and non-symbolic imaging tasks. However, since both tasks were considered simple for the adult participants, we were not able to discover whether the participants' performance on the two tasks correlated or not.

One limitation of this study was that we did not have the ability to utilize a digitizer at the time. Without a digitizer we were unable to localize to specific anatomical brain regions. Future work in this area should make use of such a tool, such that the data we are collecting becomes extremely reliable.

Consistent with our hypotheses, our findings suggest that there is a common core cognitive process for symbolic and non-symbolic, or social, division. The pattern of imaging results provides reason to believe that the innovative social division task is tapping into a similar area as a symbolic division task. Therefore, we hope to utilize these methods and administer a similar study to children ages 4 to 12. This data will help to provide a better understanding of the origins and development of mathematical competence.

Figure 1. Functional NIRS probe configuration. Probe-set and channel configuration for right and left hemispheres, respectively.

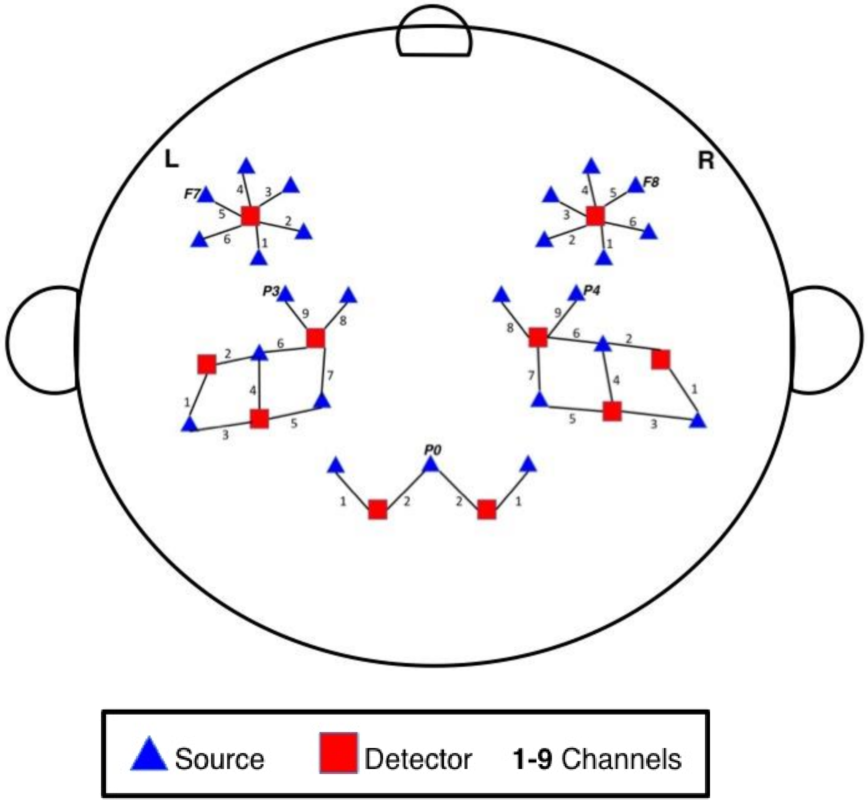


Table 1. Brain regions maximally overlaid by the probe arrangement.

Channel		Region
Left	Right	
1, 6	34, 29	MFG
2, 3	33, 32	SFG
4, 5	31, 30	IFG
7, 9	28, 26	TPJ
8, 10, 11, 12, 13	27, 24, 25, 22, 23	IPL
14, 15	20, 21	SPL
16, 17	19, 18	SOL

Figure 2. Social Division Task. Using a button-press, participants were asked to determine which animal was being nicer. (A) Baseline condition. The two animals on the screen began the trial with a different amount of candy. The one with more candy gave an outright larger number of candies and a larger proportion of its share. Thus, the animal that gave more candy to the participant is considered "nicer." (B) Absolute condition. The two animals began with a different amount of candy, but shared the same number of pieces with the participant. Thus, the animal that began with a smaller number of candies shared a larger proportion and is considered "nicer." (C) Conflict condition. The two animals began with and gave different amounts of candy. One animal gave an outright large amount of candy but a small proportion of its share, while the other animal gave a smaller outright number but a larger proportion of its share. Here, the animal that gave a larger proportion is "nicer," even though it gave a smaller number of candies to the participant. This trial requires that participants not simply look at outright amounts of candy shared, but to analyze the fraction of candy each animal has shared. A sample of each condition is shown below.

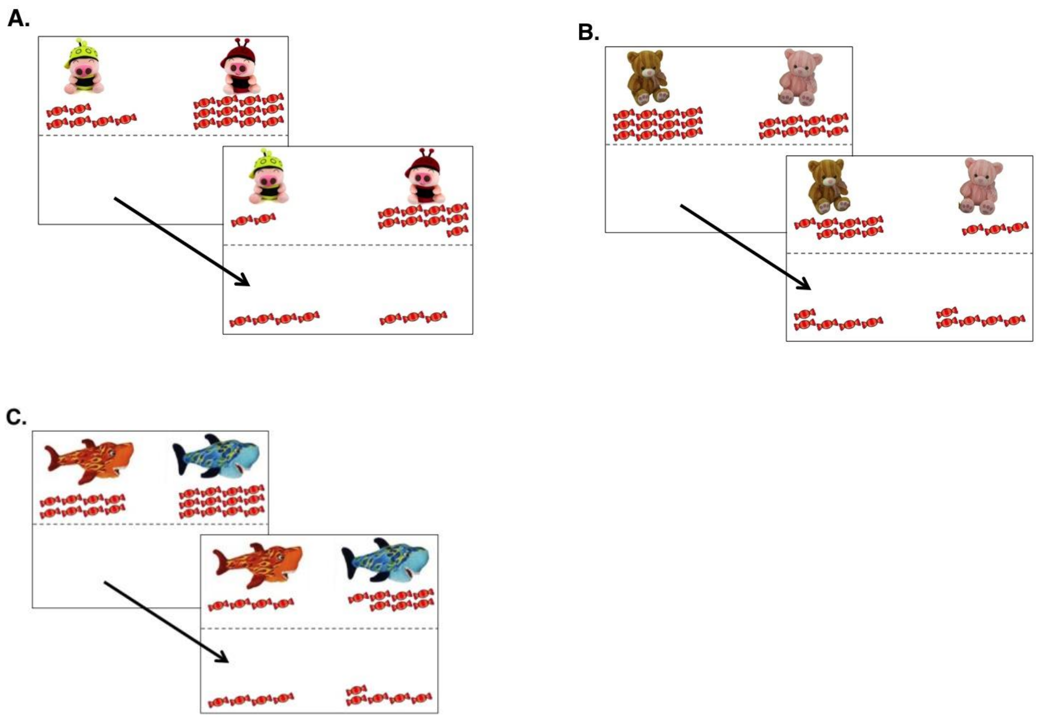


Figure 3. Symbolic Division Task. *Using a button-press, participants were shown an equation with one possible answer on the left side of the screen, and another possible answer on the right side of the screen. (A) Addition condition. Participants were shown an addition problem and were asked to determine the correct answer. (B) Subtraction condition. Participants were shown a subtraction problem and were asked to determine the correct answer. (C) Division condition. Participants were shown a division problem and were asked to determine the correct answer.*

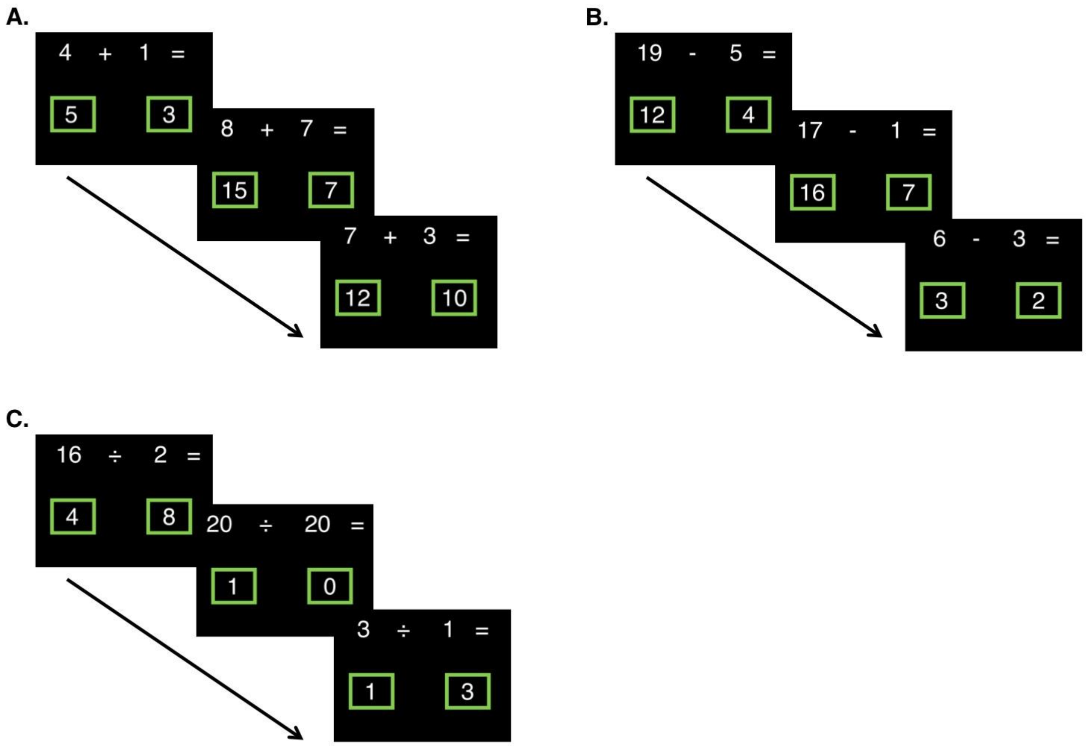


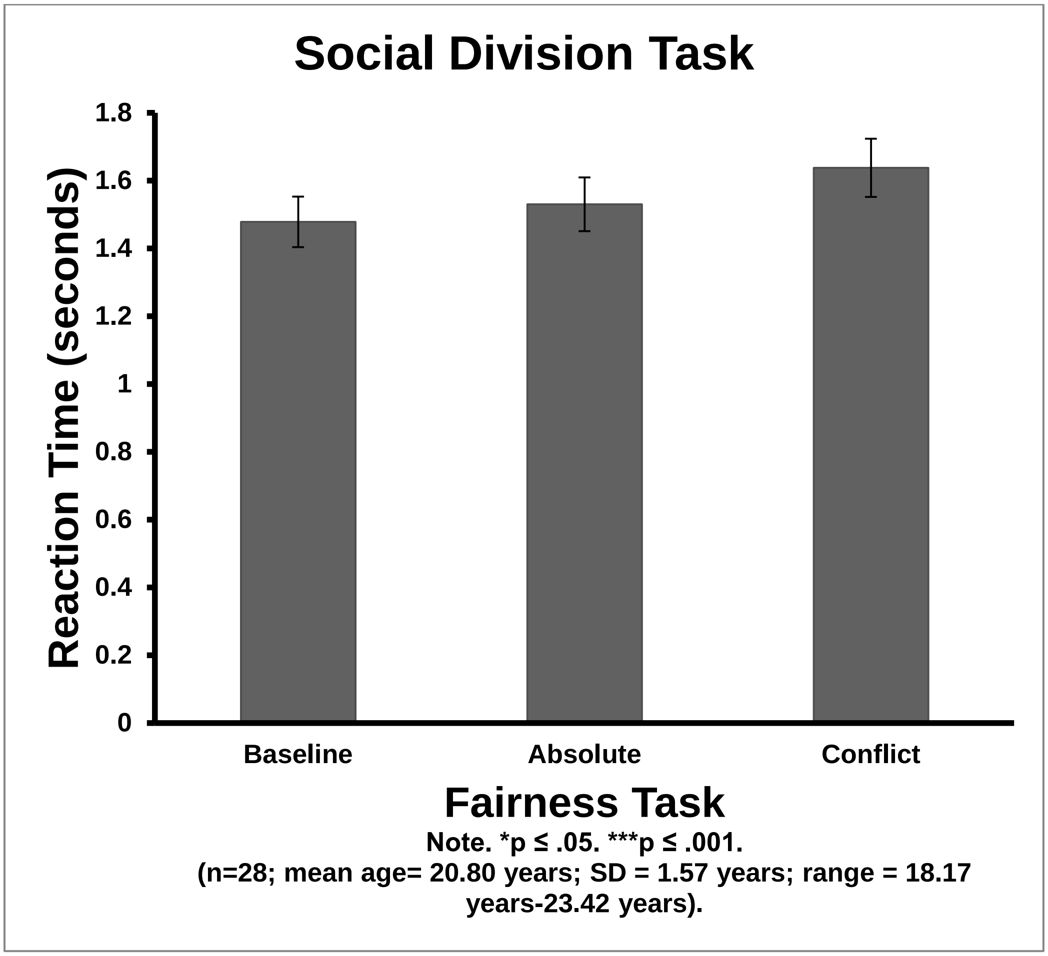
Table 2. Behavioral Measures used during the testing session.

Behavioral Measures	Task
Verbal Intelligence:	KBIT-2 Verbal
Nonverbal Intelligence:	KBIT-2 Matrices
Executive Functioning:	Head-Toes-Knees-Shoulders
Mathematical Ability:	WJ-III Subtest, Math Calculation Skills

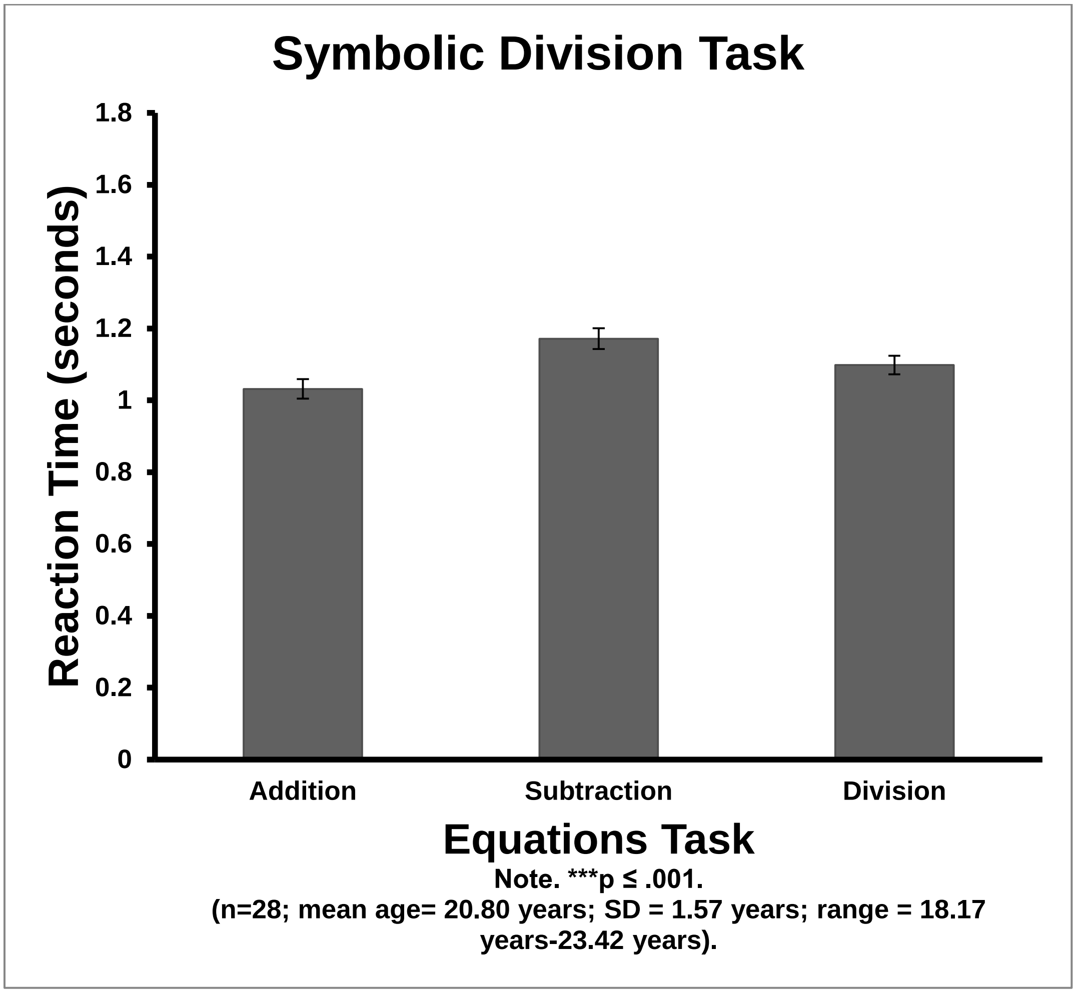
Table 3. Descriptive measures.

Descriptive Statistics on All Imaging and Behavioral Measures					
	N	Mean	SD	Min	Max
Age (Months)	28	249.64	18.882	218	281
Imaging tasks (ACC)					
Fairness Baseline	26	.96	.061	1	1
Fairness Absolute	26	.94	.087	1	1
Fairness Conflict	26	.78	.281	0	1
Equation Addition	26	.97	.035	1	1
Equation Subtraction	26	.96	.056	1	1
Equation Division	26	.94	.046	1	1
Imaging tasks (RT in ms)					
Fairness Baseline	26	1461.42	404.62	733	2277
Fairness Absolute	26	1510.69	410.85	827	2257
Fairness Conflict	26	1619.74	465.39	845	2474
Equation Addition	26	1035.52	142.05	808	1335
Equation Subtraction	26	1178.05	151.12	847	1450
Equation Division	26	1102.88	135.16	881	1378
Behavioral tasks					
WJ Calculations (Raw)	28	33.61	5.27	25	43
HTKS (Raw)	27	58.04	2.41	50	60
KBIT Verbal (Raw)	23	50.96	3.80	43	57
KBIT Matrices (Raw)	23	40.17	2.82	34	44

Graph 1. Behavioral Reaction Time bar graph for all participants during social division task.



Graph 2. Behavioral Reaction Time bar graph for all participants during symbolic division task.



Graph 3. Behavioral Reaction Time bar graph for all participants comparing control versus experimental conditions in both social and symbolic division tasks.

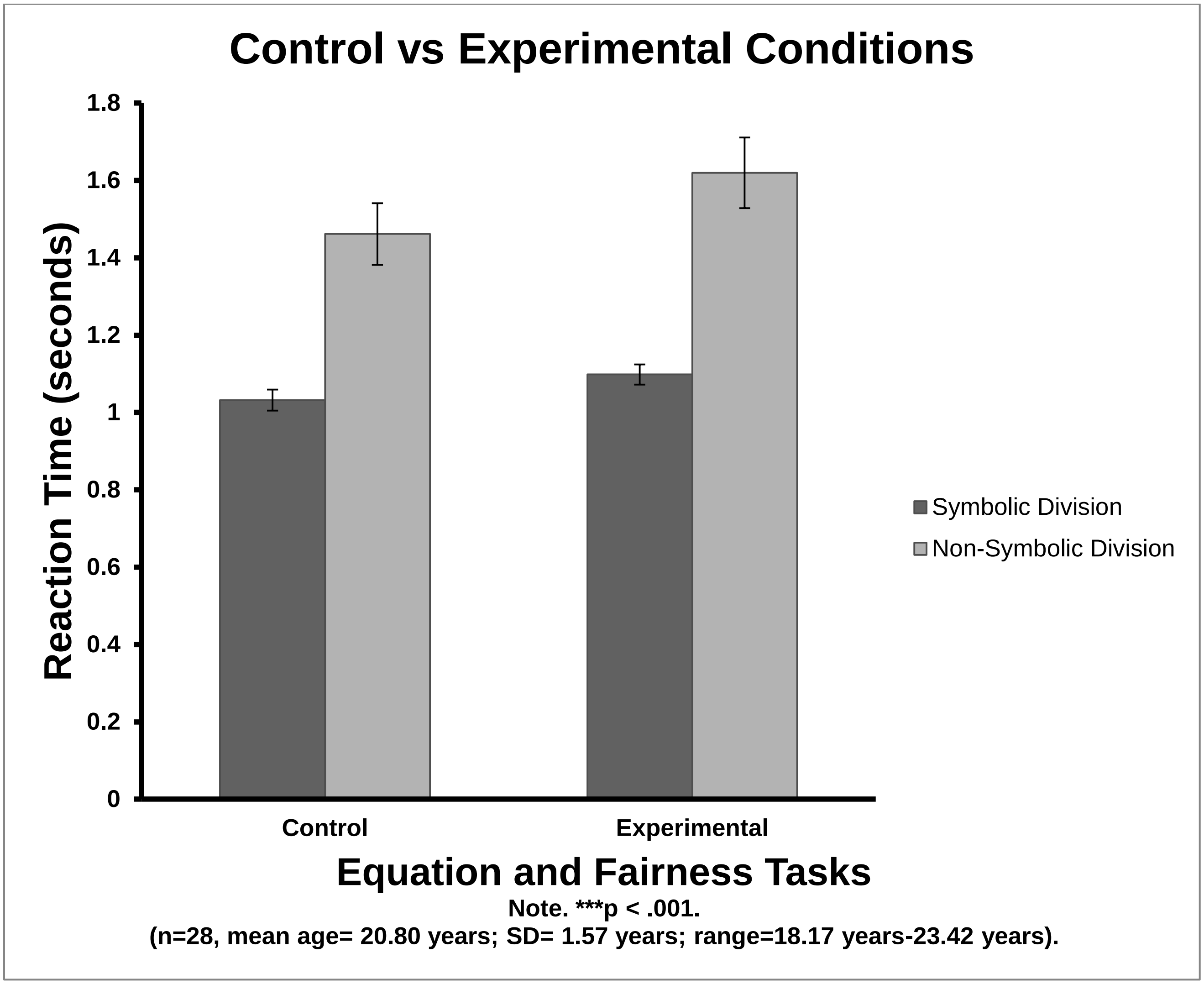


Table 4. Adult (ages 18-23) Correlations for All Imaging and Behavioral Task Measures.

Variables	***n***	***1***	***2***	***3***	***4***	***5***	***6***
1 Baseline RT (Fairness)	*26*	-					
2 Absolute RT (Fairness)	*26*	.892***	-				
3 Conflict RT (Fairness)	*26*	.890***	.889***	-			
4 Addition RT (Equation)	*26*	.231	.096	.129	-		
5 Subtraction RT (Equation)	*26*	.339†	.258	.237	.826***	-	
6 Division RT (Equation)	*26*	.349†	.283	.281	.856***	.858***	-
7 Woodcock-Johnson Calculations (Raw)	*28*	.136	.194	.238	-.015	.059	.043
8 Head-Toes-Knees-Shoulders (Raw)	*27*	-.142	.000	-.018	-.483*	-.265	-.446*
9 KBIT Verbal Knowledge (Raw)	*23*	-.708***	-.665***	-.590**	-.297	-.241	-.319
10 KBIT Matrices (Raw)	*23*	-.002	.042	.117	-.663**	-.442*	-.433*

*Note. †p≤ .10. *p* ≤ .05. ***p* ≤ .01. ****p* ≤ .001.

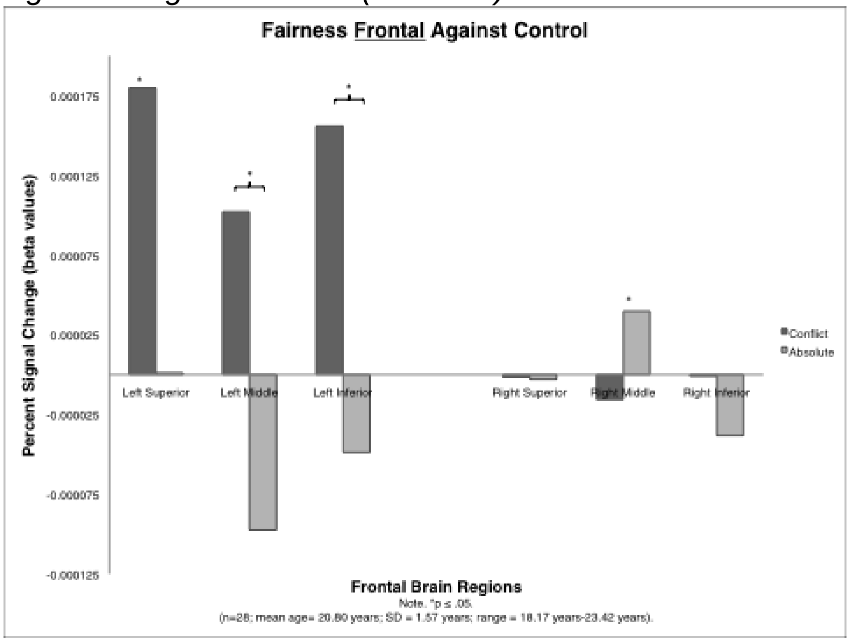
*Table 5. HbO Beta Values for Social Division Task. Note. *remained significant after FDR correction.*

Channels	Conflict-Absolute	Conflict-Baseline	Absolute-Baseline
1	1.83E-06*	1.25E-06	-5.73E-07
2	1.75E-06	1.97E-06*	2.27E-07
3	1.83E-06*	1.63E-06*	-2.05E-07
4	2.60E-06*	1.93E-06*	-6.68E-07
5	1.50E-06*	1.19E-06	-3.09E-07
6	2.17E-06*	7.90E-07	-1.38E-06*
7	3.71E-07	1.73E-06*	1.36E-06*
8	-6.19E-07	1.50E-06*	2.12E-06*
9	6.32E-07	8.61E-07*	2.29E-07
10	-1.11E-07	1.32E-06*	1.43E-06*
11	-2.33E-05	1.12E-05	3.45E-05
12	-6.99E-08	1.20E-06*	1.27E-06*
13	-2.43E-05	2.32E-05	4.75E-05
14	-8.89E-07	9.17E-07	1.81E-06*
15	-1.27E-06*	9.78E-07*	2.25E-06*
16	-1.19E-06	3.87E-07	1.57E-06
17	-9.74E-07*	6.66E-07	1.64E-06*
18	-2.69E-07	3.79E-07	6.48E-07
19	-4.65E-07	2.63E-07	7.28E-07
20	-9.23E-07	4.32E-07	1.35E-06*
21	-6.04E-07	1.22E-06	1.82E-06*
22	-6.86E-07	1.49E-06*	2.18E-06*
23	-5.58E-07	1.01E-06*	1.57E-06*
24	1.98E-07	1.57E-06*	1.38E-06*
25	7.82E-07	2.05E-06*	1.27E-06
26	-7.09E-07	1.18E-06	1.89E-06*
27	2.60E-07	1.13E-06	8.74E-07
28	1.14E-06*	2.01E-06*	8.62E-07
29	5.87E-07	-2.37E-07	-8.24E-07*
30	-2.91E-07	1.03E-07	3.95E-07
31	1.05E-06*	-1.09E-07	-1.16E-06*
32	2.35E-07	-5.38E-07	-7.73E-07
33	-2.08E-07	5.05E-07	7.14E-07
34	-1.69E-06	-7.66E-08	1.62E-06*

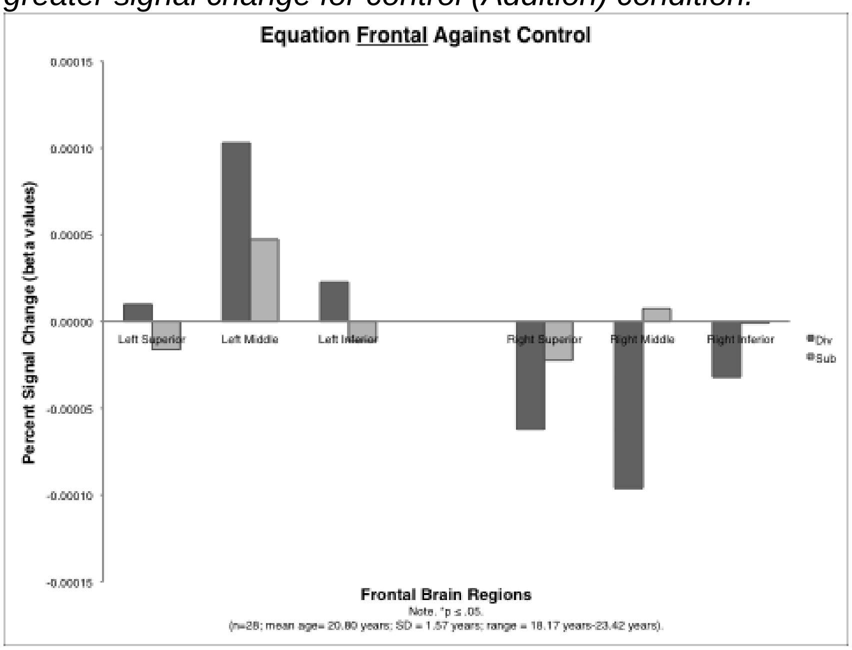
*Table 6. HbO Beta Values for Symbolic Division Task. Note. *remained significant after FDR correction.*

Channels	Division-Addition	Subtraction-Addition	Division-Subtraction
1	7.53E-07	2.42E-07	5.11E-07
2	5.74E-08	-3.86E-07	4.43E-07
3	1.40E-07	6.25E-08	7.78E-08
4	2.86E-07	-1.07E-07	3.94E-07
5	1.67E-07	-1.24E-07	2.91E-07
6	1.31E-06	7.06E-07	6.01E-07
7	3.38E-07	1.99E-07	1.39E-07
8	1.35E-06	4.54E-07	8.95E-07
9	-1.93E-06*	-1.13E-06	-7.96E-07
10	3.00E-07	6.14E-07	-3.14E-07
11	-5.21E-07	-1.08E-07	-4.13E-07
12	7.90E-07	4.01E-07	3.89E-07
13	8.18E-07	-1.89E-08	8.37E-07
14	5.67E-07	9.44E-07	-3.77E-07
15	-1.58E-07	2.78E-07	-4.36E-07
16	4.69E-08	-2.21E-07	2.68E-07
17	-1.54E-06*	-4.81E-07	-1.06E-06
18	-2.44E-06	-1.10E-06	-1.34E-06
19	-1.79E-06	-7.14E-07	-1.08E-06
20	-4.76E-07	-2.51E-07	-2.25E-07
21	1.17E-07	-1.50E-07	2.67E-07
22	7.28E-07	-7.25E-07	2.87E-09
23	-2.84E-07	-5.42E-08	-2.30E-07
24	-1.90E-06*	-3.40E-07	-1.56E-06
25	-1.90E-06*	-4.36E-07	-1.46E-06
26	-2.54E-06*	-2.59E-06	5.54E-08
27	-1.28E-06	-1.14E-06	-1.36E-07
28	-2.15E-06*	-9.95E-07	-1.15E-06
29	-1.12E-06	-2.56E-07	-8.65E-07
30	-3.13E-07	2.16E-07	-5.29E-07
31	-3.28E-07	-2.21E-07	-1.07E-07
32	-3.64E-07	-2.80E-07	-8.41E-08
33	-8.76E-07*	-1.67E-07	-7.09E-07
34	-8.00E-07	4.04E-07	-1.20E-06*

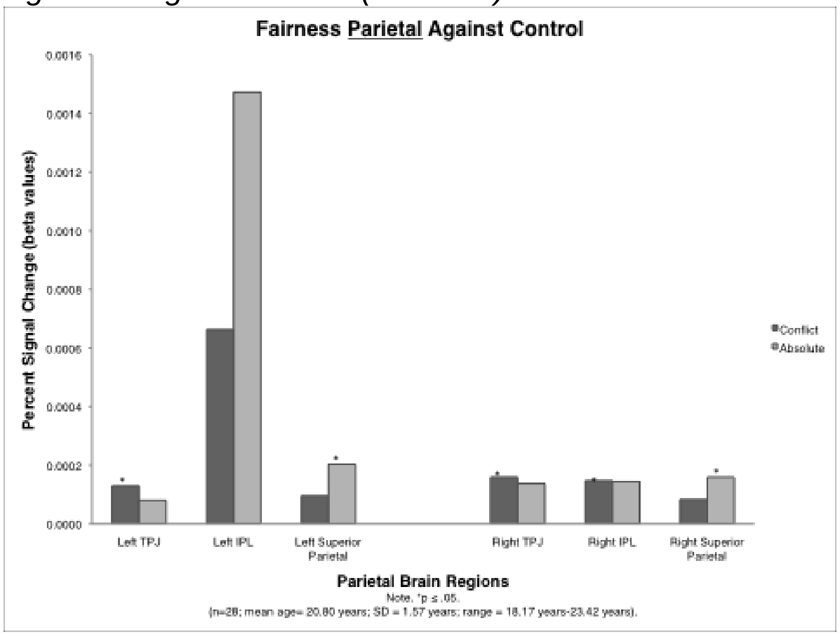
Graph 4. Frontal lobe activation in Social Division Task. Graph displays subtractive comparisons of all three conditions. Positive values represent greater original change for experimental (Absolute or Conflict) condition, and negative values represent greater signal change for control (Baseline) condition.



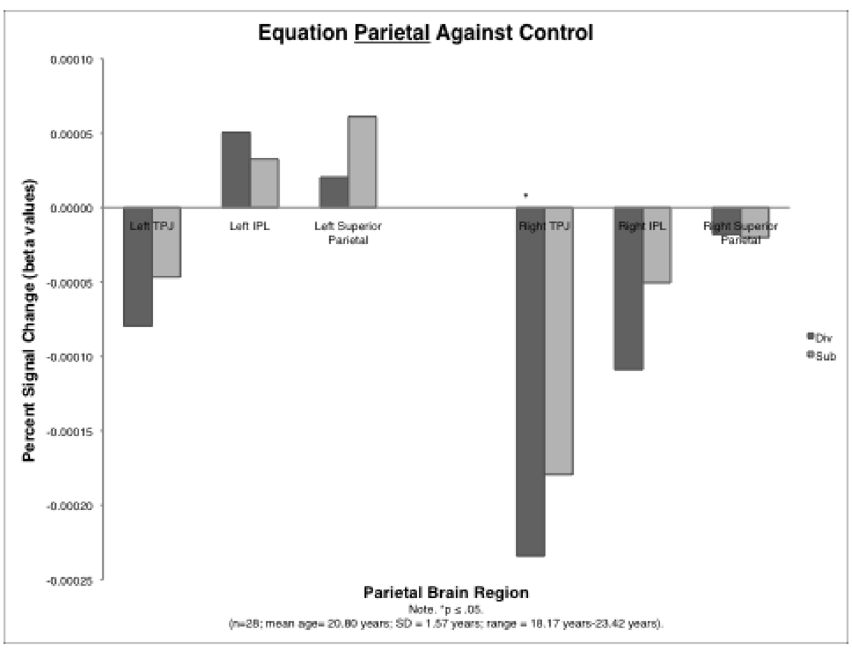
Graph 5. Frontal lobe activation in Symbolic Division Task. Graph displays subtractive comparisons of all three conditions. Positive values represent greater original change for experimental (Subtraction or Division) condition, and negative values represent greater signal change for control (Addition) condition.



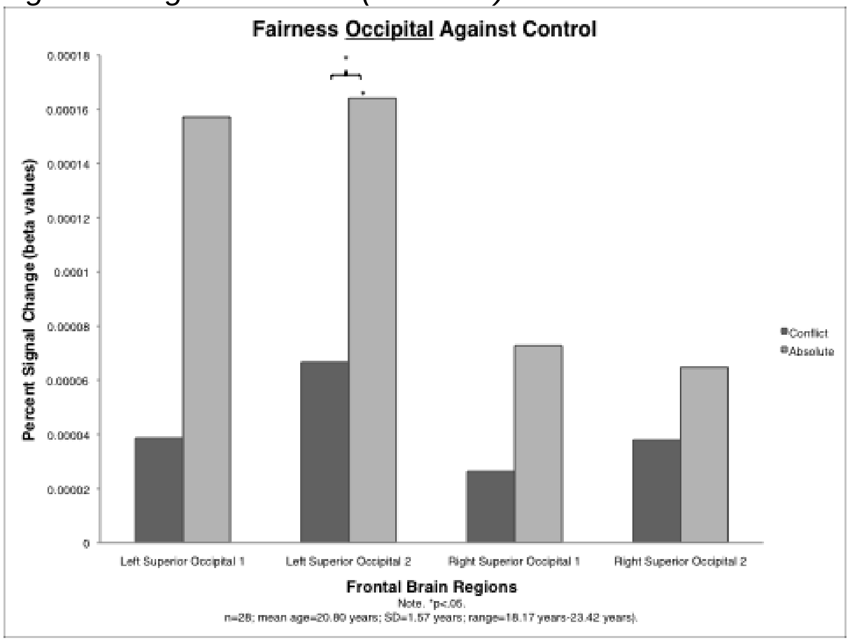
Graph 6. Parietal lobe activation in Social Division Task. Graph displays subtractive comparisons of all three conditions. Positive values represent greater original change for experimental (Absolute or Conflict) condition, and negative values represent greater signal change for control (Baseline) condition.



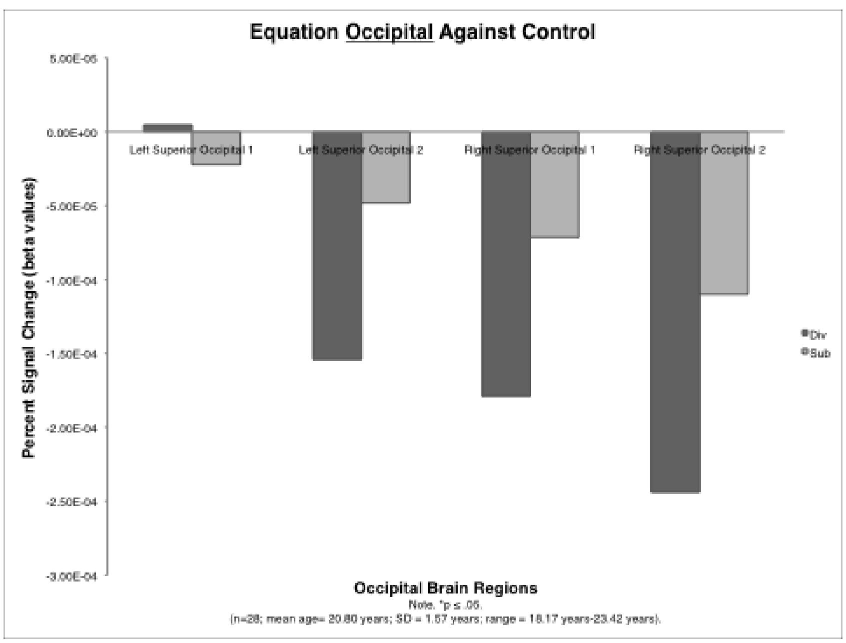
Graph 7. Parietal lobe activation in Symbolic Division Task. Graph displays subtractive comparisons of all three conditions. Positive values represent greater original change for experimental (Subtraction or Division) condition, and negative values represent greater signal change for control (Addition) condition.



Graph 8. Occipital lobe activation in Social Division Task. Graph displays subtractive comparisons of all three conditions. Positive values represent greater original change for experimental (Absolute or Conflict) condition, and negative values represent greater signal change for control (Baseline) condition.



Graph 9. Occipital lobe activation in Symbolic Division Task. Graph displays subtractive comparisons of all three conditions. Positive values represent greater original change for experimental (Subtraction or Division) condition, and negative values represent greater signal change for control (Addition) condition.



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