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Exploring the Neural Basis of Selective and Flexible Dimensional Attention: An fNIRS Study

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ABSTRACT

Between the ages of 3 and 5, children develop greater control over attention to visual dimensions. Children develop the ability to flexibly shift between visual dimensions and to selectively process specific dimensions of an object. Previous proposals have suggested that selective and flexible attention is developmentally related to one another. However, the relation between flexibility and selectivity has not been systematically probed at the behavioral and neural levels. We administered a selective attention task (triad classification) along with a flexible attention task (dimensional change card sort) with 3.5 -and 4.5-year-olds while functional near-infrared spectroscopy data were recorded. Results showed that children with high flexible attention skills engaged the bilateral frontal cortex which replicates previous studies using this task. Moreover, children with high levels of selective attention engaged the right frontal cortex. Together, these results indicate that development in the right frontal cortex is important for both flexible and selective dimensional attention.

Introduction

Attention is a central aspect of cognition utilized to select which information should be processed, enhance processing of task-relevant information, or otherwise guide cognitive processing in a goal-directed fashion. The development of attention is protracted, unfolding from infancy through adolescence, and is predictive of quality of life outcomes as well as academic success (Cuevas & Bell, 2014; Moffitt et al., 2011). However, the study of attention is complicated by a lack of data regarding the neural mechanisms involved in different types of attentional functions. In this report, we examine a specific aspect of attention: attention to visual dimensions. This form of attention is relevant when a specific aspect of a stimulus, such as the shape or color, is relevant for a given task. We examine this form of attention in the context of explicit rule-based guidance of attention and implicit similarity-based guidance of attention. We take a cognitive neuroscience approach to explore whether common or distinct neural mechanisms give rise to different behaviors related to attention to visual dimensions.

One task that gauges the developmental status of dimensional attention in early childhood is the dimensional change card sort task (DCCS). In this task, children are explicitly

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The data that support the findings of this study are available from the corresponding author upon reasonable request.

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instructed to sort test cards to sorting locations marked by target cards. Each test card matches both the target cards along separate dimensions. Children are instructed to sort by either shape or color in the pre-switch phase and then instructions are given to switch to sort by the other dimension in the post-switch phase (see Figure 1a). The DCCS reveals robust developmental differences in performance between 3- and 4-year-olds (Zelazo, Muller, Frye, & Marcovitch, 2003; for a review see, Buss & Spencer, 2014). That is, 3- and 4-year-olds typically have no difficulty sorting during pre-switch trials. During post-switch trials, however, 3-year-olds tend to perseverate, while 4-year-olds have little difficulty flexibly switching attention to sort by the new rules.

Performance on the DCCS task has previously been linked to activation along a frontal-temporal-parietal network in adolescence and adulthood (Morton, Bosma, & Ansari, 2009). During early childhood, children who fail to switch rules show weak activation along this network. When children develop the ability to use rules to switch attention, this network of regions is engaged more strongly (Buss & Spencer, 2018; Moriguchi & Hiraki, 2009, 2011). Interestingly, Buss and Spencer (2018) showed that activation in the frontal cortex during early childhood varies based on task demands. This study administered the standard DCCS task along with an "easier" version of the task which has been previously

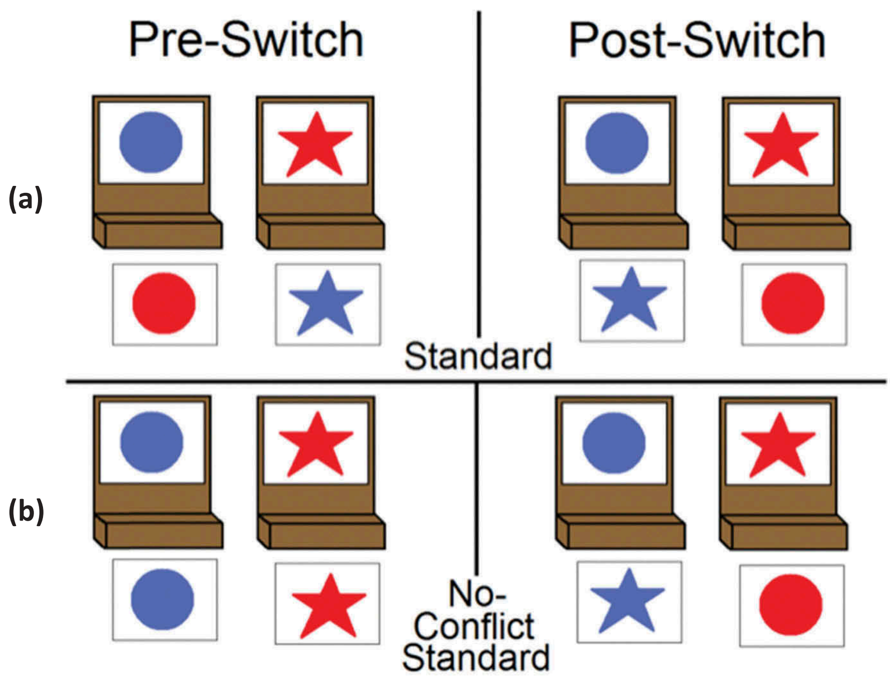


Figure 1. A, an example of the standard DCCS. B, an example of the no-conflict version of the DCCS (Buss & Spencer, 2018).

shown to present little difficulty to 3-year-olds. This easy version uses no-conflict cards during the pre-switch phase. That is, if the target cards contain a blue star and a red circle, then children would sort test cards that also contain either a blue star or a red circle (see Figure 1b). During the post-switch trials, children are given the standard test cards that contain visual conflict. The success of young children in this condition is due to the post-switch features being sorted to the same location for both the pre- and post-switch phases. That is, during the pre-switch trials, children learn about where the post-switch features will need to be sorted after the rules change. As illustrated by Buss and Spencer (2018), this manipulation also has a robust impact on activation within the frontal cortex. Specifically, children who perseverate in the standard task and fail to show frontal activation when doing so, nonetheless, show strong activation in this region when correctly switching in this "easy" version of the task.

Buss and Spencer (2018) explained these results using a dynamic field (DF) model. This model simulates frontal–posterior interactions in the context of object representation processes and dimensional label processes. Object representation processes arise from posterior cortical interactions between temporal and parietal populations that are involved with the binding of features to spatial locations. Label representation processes arise from frontal regions that associate labels with visual features and enhance activation of task-relevant visual features in posterior cortical populations. That is, by activating representations of labels such as "color" or "shape", processing of the associated visual dimension within the object representation system becomes enhanced. In the standard version of this task, children are given explicit instructions about which features should be used to sort cards. These explicit instructions activate dimensional label representations that provide top-down input to object representation areas. During the pre-switch phase, the model uses this top-down support to sort by the instructed dimension and the object representation system accumulates memory traces for which features were sorted to which locations. As illustrated in Figure 1a, if sorting by shape during the pre-switch phase, children would form memories for red and circle being sorted to the left, and blue and star being sorted to the right. During the post-switch phase, however, these memory traces will interfere with the ability to bind those features to the opposite spatial location when being instructed to sort by color. That is, the model will have memories binding red and circle to the left, but will be required to sort red and circle to the right during the post-switch trials. With weak coupling between labels and visual features, the model will have weak top-down modulation of attention. In this case, the model will perseverate and show weak frontal activation. With strong coupling between labels and visual features, the model will more strongly activate dimensional label representation, further enhancing processing within the task-relevant population. In this case, the model will be able to switch rules and will show strong frontal cortex activation.

The "easy" version of the task leverages memories of feature-space bindings that form in posterior brain regions to drive activation within the frontal cortex in a bottom-up fashion. For example, when sorting red to the rightward location during the pre-switch phase, as illustrated in the No-Conflict version in Figure 1b, memories build up in the posterior cortex that associate the red feature with the rightward spatial location. If red cards also need to be sorted to the rightward location during the post-switch phase, then these memories will overlap with the task structure (i.e., red being present at the rightward target card location) which will result in a strong feature-space representation of red at the rightward location. As a result, a strong bottom-up signal will be sent to the frontal cortex, leading to stronger activation of the frontal cortex. In this way, the No-Conflict version taps into a form of implicit attention that is guided by the influence of memories and task inputs within object representation areas of the brain. Thus, the data from Buss and Spencer (2018) illustrate that the same region of the frontal cortex that is activated when children switch rules using rule-based top-down attention in the standard task is also activated when children, who otherwise fail in the standard task, switch rules in the easier version of the task that relies upon bottom-up, implicit attentional processes. From the perspective of the DF model, explicitly guided attention and implicitly guided attention may share a common neural substrate in the frontal cortex.

The above example of an "easy" version of the DCCS, implicit and explicit attention is intertwined because children are still instructed to sort by a specific set of rules. Thus, the data are not clear regarding the extent to which frontal activation is associated with explicit or implicit attention. The same DF model used to explain DCCS performance and activation has also been used to explain other forms of dimensional attention that are directly designed to be implicit and do not have an explicit component (Buss & Kerr-German, 2019). For example, in the triad-classification (TC) task (Smith & Kemler, 1977) children are presented with a reference object that has two stimulus features that could be relevant (e.g., shape and color). Then, two choice objects appear under the reference object from which children are instructed to pick the item that "goes best with" or is "most similar to" the reference object. The choice objects are designed to pit holistic feature processing against selective feature processing. Specifically, the *holistic* object is not exactly the same as the reference object along either dimension but is similar along both. The *identity* object, on the other hand, is exactly the same along one dimension but is maximally different along the other. Thus, if children are able to selectively attend to a single feature dimension, then they should be able to select the identity object. However, if they are unable to selectively attend, then they will integrate information along both dimensions and will select the holistic item. In general, previous research suggests that selective attention, and the rate of choosing the identity object, increases over development (Smith & Kemler, 1977).

The DCCS task and the TC task present distinct processing demands. In the DCCS task, there is a consistent feature-space mapping that children use during the pre-switch phase (e.g., circle is sorted to the left and star is sorted to the right) that build up habits in object representation areas. Additionally, a consistent dimension is relevant for the initial sorting phase, and children must switch to using the other dimension during the post-switch phase. Thus, a strong modulation of the relevant visual dimension, driven by the top-down activation of the dimensional label that is relevant for the post-switch phase, is needed to overcome the feature-space memories that have accumulated during the pre-switch phase. In the TC task, however, children cannot anticipate from one trial to another which dimension should be attended and the relevant dimension must be inferred based on the configuration of the stimuli. In this way, successful performance in this task requires the ability to infer the relevant dimension in an implicit fashion. Despite these differences in processing demands, previous research has demonstrated an association in performance on these two tasks. Buss and Kerr-German (2019) showed that children who were able to flexibly switch rules in the DCCS task also selected the identity object at a significantly higher rate compared to children who perseverated.

From the perspective of the DF model, the TC task taps into similar object representation processes that were discussed above in relation to the No-Conflict version of the DCCS. That is, the ability to infer the relevant dimension in the TC task arises from the overlap of inputs provided by the task in the posterior cortex which then provides a signal to the frontal cortex about which dimension is relevant. For example, if the identity object matches the reference object along the dimension of color, then the population of neurons that represents the visual dimension of color will have greater neural output relative to the population of neurons that represents the visual dimension of shape. If the coupling between labels and visual features is sufficiently strong, the object representation system will send a strong input to the frontal label representation system to activate the associated dimensional label representation. Once a label representation is activated, processing of the associated visual dimension will become enhanced, and a decision will be made to select the identity object. In the absence of strong feature-label associations, the model will not be able to recruit dimensional attention to guide the decision-making process and will be more likely to select the holistic item (see Buss & Kerr-German, 2019 for further details about the model).

Based on this previous simulation work, the DF model predicts that common neural mechanisms should be engaged when children are successful on either of these tasks. In this report, we administered the DCCS and TC tasks while functional near-infrared spectroscopy (fNIRS) data were collected from 3- and 4-year-olds. To preview the results, there were differences in neural activation as a function of children's success on both tasks. Importantly, for children who were successful on either task, a common region of activation was identified in the right lateral frontal cortex. We suggest that this region is responsible for guiding dimensional attention in both a top-down and bottom-up fashion.

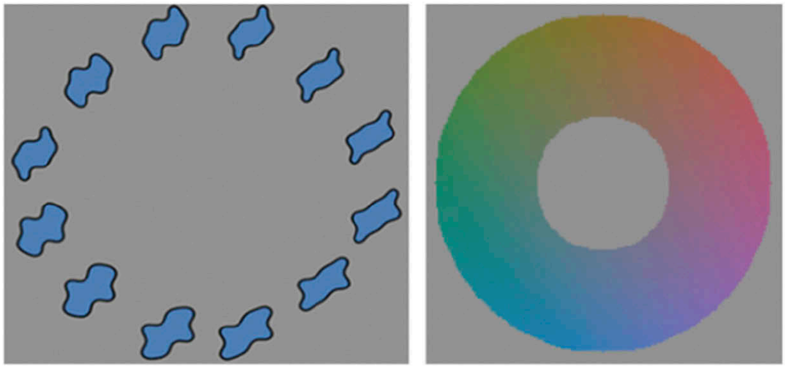
Materials and methods

Participants

A total of 45 children were recruited into the study. Six children were dropped due to technological failures. An additional three children were dropped for failure to complete both tasks. One child was dropped for failure to complete the tasks while wearing the fNIRS cap. Two children were dropped due to excessively long RTs (greater than 12 seconds on 40% of trials). An additional two children were dropped for failing the pre-switch trials. Lastly, one child was dropped for losing all data after wavelet filtering for the DCCS task. The final data set included 31 children. Fifteen 3.5-year-olds (mean age = 42.69 mo; 10 females) and 16 4.5-year-olds (mean age = 52.71; 5 females) were included in the final analyses. All parents or legal guardians signed an informed consent document and all methods were approved by the University of Tennessee IRB.

Stimuli

Stimuli in the TC consisted of objects composed of visual features that could be metrically controlled. Shapes were defined using Fourier space (see Figure 2a,b; Drucker & Aguirre, 2009), and colors were defined in CIELab space. A set of 3,600 objects was used, where colors and shapes were each stepped in 6° increments for 60 steps. On each trial, an object



(a) (b)

Figure 2. On the top left (a) is an example of shape space used in this task and on the top right (b) is color used in this task from CIELab.

was randomly selected from this subset of objects to be used as the reference object. The ID object was then chosen to be exactly the same as the target object along either the color or shape dimension (i.e., matching in degree the shape or color of that dimension from the aforementioned set of objects), depending on which dimension was relevant for each trial (i.e., color match or shape match trials). The other dimension of the ID object was selected to be 180° different in feature-space. The features of the holistic object were chosen to be between 90° and 114° different along both dimensions. Pilot data from this task demonstrated that adult participants will select the identity object on more than 85% of trials with these configurations of stimuli (Buss & Kerr-German, 2019).

In the DCCS task, a yellow fish and purple house were used as target cards during the pre- and post-switch phases. Test cards during these phases consisted of yellow houses and purple fish. During the mixed block, red bunnies and green chairs were used as target cards and test cards consisted of green bunnies and red chairs (see Figure 3). For all phases (pre-switch, post-switch, mixed block), the two target cards were presented on images of two trays.

Procedure

Children sat on a chair in front of a touch screen computer monitor. The child's head was measured, they were capped with the appropriate fNIRS cap (i.e., 52–54 cm in diameter with associated scaled probe configurations), and a digitization of the probe on the child's head was made. The locations of the sources and detectors were digitized using a Polhemus motion tracking system and marked in relation to landmarks (nasion, inion, left tragus, right tragus, and vertex) to map probe placements (see Figure 4).

Children were administered both tasks in counterbalanced order. The order of dimensions was also counterbalanced for the DCCS. In the DCCS, children were first given the dimensional rules for the pre-switch trials: "We are going to play the color game. In the color game, we sort by color. That means purple ones go here, and yellow ones go here (*pointing to right and left target cards*)." Children were given two

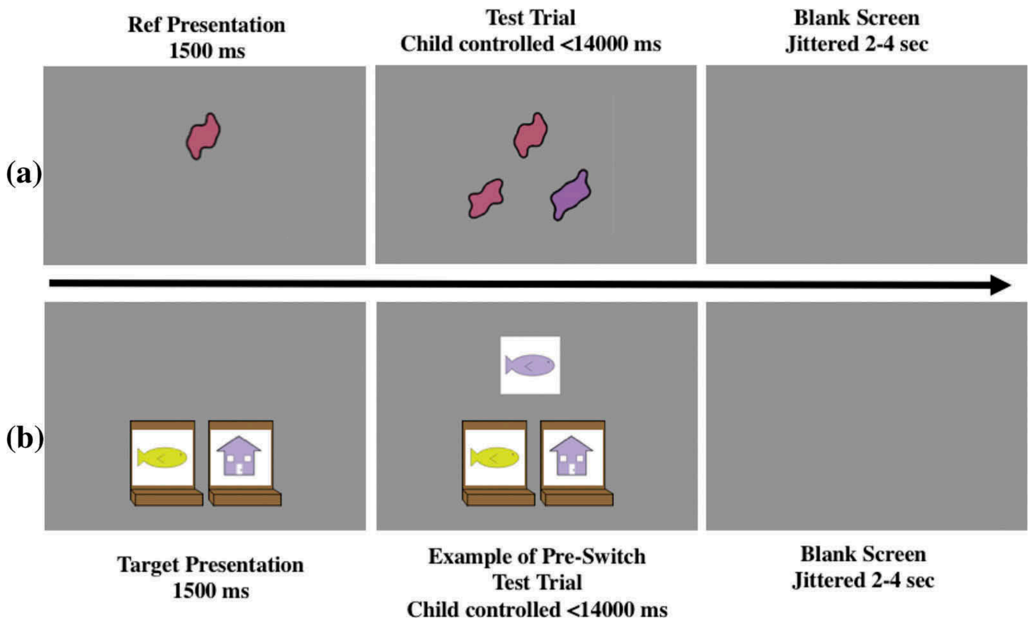


Figure 3. This figure depicts the sequence of events from one trial of the TC (top) task and one trial from the pre/post-switch blocks in the DCCS (bottom).

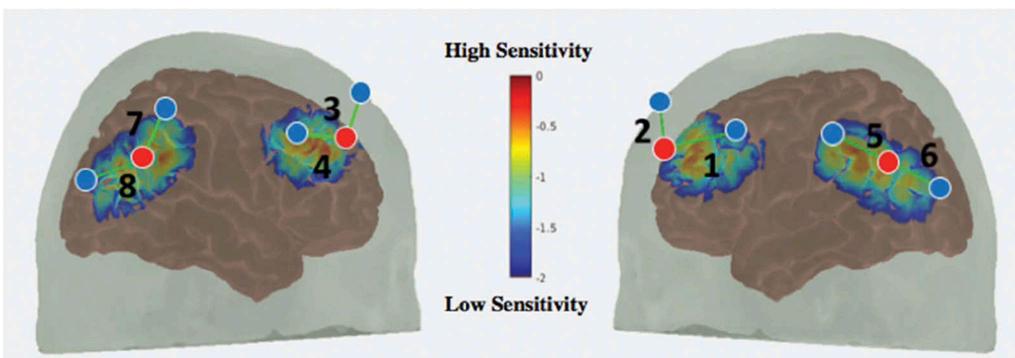


Figure 4. Sensitivity profiles for fNIRS probe used in the current study.

demonstration trials during which the experimenter showed the child how to sort by the pre-switch rules. Demonstrations were not provided during any other phase of the task. Children were then presented with a series of test cards and the experiment asked, "In the color game, where would this one go (*pointing to the test card*)?". After the pre-switch trials, children were then told to stop playing the pre-switch game and were instructed in a similar fashion for the post-switch rules. Within the mixed block, children were given 30 trials, 20 of which they were instructed to sort by the post-switch dimension. For example, if the pre-switch dimension was color, 10 out of 30 trials would instruct children to use the color rules, and 20 out of 30 trials would instruct children to use the shape rules.

Children were given the following instructions for the TC task: "you are going to see one object appear on the screen and then two more just above it, here (*pointing above*). I want you to tell me which one of these two (*pointing to the left and the right*) goes most with or is most like this one (*pointing to reference object*)." Children were instructed to use their finger to tap their choice on a touch screen monitor and were reminded of the instructions as needed throughout the tasks. Children were given two practice trials in the beginning that were not included in subsequent analyses and a total of 64 experimental trials.

fNIRS data collection

Functional near-infrared spectroscopy (fNIRS) was collected at 25 Hz using a Techen CW6 system with wavelengths of 830 nm and 690 nm. Light was delivered via fiber optic cables that terminated in an array compiled of 4 sources and 8 detectors placed 3 cm apart for a total of 8 channels. Placement of sources was relative to the 10–20 system over the left and right frontal cortex (F3-F5; F4-F6), right parietal cortex (P4-P6), and left temporal-parietal cortex (T5-P3; see also Figure 4). Specifically, the right side was placed to target the parietal cortex whereas the left was placed to target the temporal cortex.

Behavioral analysis

We administered the DCCS as described in Zelazo and Bauer (2013). This version uses a mixed block after the post-switch phase which provides a continuous score of children's ability to switch attention. Thus, the DCCS scores were calculated using both pass/fail criteria and a continuous score. Children were grouped as passing (i.e., "switchers") if they sorted at least 4 out of 5 post-switch trials correct and as failing (i.e., "perseverators") otherwise. The continuous score was calculated as the percentage of correctly performed trials across all three phases of the task (i.e., pre-switch, post-switch, mixed)

For the TC task, children were scored in a similar fashion. The continuous score for the TC was calculated as the percentage of trials on which participants selected the ID object. Children were also grouped as "high" or "low" performers based on whether they selected the ID object more or less than 70% of trials, respectively (this value was selected to provide a more even split of participants between the "high" and "low" groups). By grouping children into groups based on performance, we can more easily assess differences in neural activation associated with improved performance on the TC task.

fNIRS data analysis

The DCCS task as typically administered with children is not optimized for neural data collection due to the blocked nature of trial types and the inability to administer multiple repetitions of the task. In previous fNIRS studies with the DCCS task, variations of the task were used that featured multiple iterations of the task (Buss & Spencer, 2018; Moriguchi & Hiraki, 2009) but are time-consuming to administer. Since the primary focus of the current project is to provide an initial exploration of the neural basis of selective attention, we opted to administer the task in typical fashion based on the NIH Toolbox version (Zelazo & Bauer, 2013) with a one pre-switch phase, one post-switch phase, and one mixed block. To simplify the analysis of the neural data, we only analyzed neural activation during the pre- and post-switch phases which had clearly focused cognitive demands. Moreover, since we only have a single block of trials for each phase, we averaged the neural data over the course of the first 30 s of each phase of the task (30 s was the longest amount of time that could be included based on how long individual children took to complete each phase of the task). Data from the pre-switch phase were then subtracted from that of the post-switch and mixed trial phases to calculate the change in cortical oxygenation associated with the transition to the post-switch phase.

Behavioral and neural findings from the DCCS are already well established in the literature. Thus, our primary focus was on the neural basis of selective attention in the TC task and associations with behavioral and basic neural findings in the DCCS. Thus, we administered a long version of the TC task that allowed us to collect data from many trials so that we could generate robust estimates of neural activation during this task. We optimized this task for event-related analyses, including multiple repetitions of each trial type and jittered timing between trials. The average amplitude of oxygenated hemoglobin (HbO_2) and deoxygenated hemoglobin (HbR) were calculated for each trial type on each channel within the time range of 0–6 seconds post trial-onset to capture the peak of the hemodynamic response in this age group (Whiteman, Santosa, Chen, Perlman, & Huppert, 2017). Trials in the TC task were excluded from the final NIRS analysis if reaction time exceeded 14 seconds in length. On average, 1.08 trials on the TC were dropped per participant based on this criterion.

In the analyses of fNIRS data below, both HbO and HbR are analyzed together for each channel. Activation is defined as a significant positive increase in HbO compared to a negative decrease in HbR. This definition reduces the risk of reporting false positives and false negatives from hemodynamic results (e.g., Tachtsidis & Scholkmann, 2016). For each task, we grouped children based on their behavioral performance and used this grouping as a between-subject factor. EasyNIRS was used for all pre-processing of data. Data were first converted to an optical density measure. We used an interquartile range of 0.5 with a wavelet-based motion artifact removal tool within EasyNIRS to correct motion artifacts in the data. Next, data were band-pass filtered (high-pass filter = .019, low-pass filter = .5) before converting to absolute concentration values using the modified Beer–Lambert equation (DPF values of 6.0 and 6.0 were used). Mixed-factor ANOVAs were used to analyze changes in hemoglobin (HbO and HbR) in relation to grouping based on performance in each task.

Results

Behavioral

Behavioral data from this study were previously reported in Buss and Kerr-German (2019). For the participants that were included in the fNIRS analyses below, the rate of choosing the ID object (i.e., percent correct) in the TC task was statistically different between 3-year-olds (M = 0.66) and 4-year-olds (M = 0.77), $t(29) = -2.153$, $p = .041$. In the DCCS task, significantly more 4-year-olds (12/16) were categorized as switchers compared to 3-year-olds (5/15), $\chi^2(1) = 4.858$, $p = .028$, replicating developmental differences typically seen with this task (Zelazo, 2006). Grouping children as switchers and perseverators in the DCCS task showed that switchers (M = 0.78) selected the ID object in the TC task at a significantly higher rate compared to perseverators (M = 0.67), $t(29) = -2.244$, $p = .033$. Further, the total percentage of correctly performed trials in the DCCS task was positively correlated with the percentage of trials on which children selected the ID object in the TC task, $r^2 = .520$, $p = .003$ (see Figure 5).

Hemodynamic results in the DCCS

First, pre- and post-switch blocks were analyzed. Analyses of the fNIRS data revealed interactions between chromophore (HbO, HbR) and performance on the DCCS task on channel 2 over left frontal cortex, $F(1,29) = 4.727$, $p = .038$, $\mu^2 = .140$, channel 3 over right frontal cortex, $F(1,29) = 5.172$, $p = .031$, $\mu^2 = .151$, and channel 4 over right frontal cortex, $F(1,29) = 7.762$, $p = .009$, $\mu^2 = .211$. Follow-up analyses on all of these channels showed that there was significantly stronger switching-related increases in HbO for the group of children that switched compared to the group of children that perseverated ($t(29) = 2.173$, $p = .038$ for channel 2, $t(29) = 2.145$, $p = .040$ for channel 3, and $t(29) = 2.386$, $p = .024$ for channel 4; see Figure 6). No other effects reached significance.

Hemodynamic results in the TC

Analyses of the fNIRS data revealed a main effect of Oxy on channel 1 over left frontal cortex, $F(1,29) = 9.145$, $p = .005$, $\mu^2 = .24$, channel 2 over left frontal cortex, $F(1,29) = 15.913$, $p < .001$, $\mu^2 = .354$, and channel 4 over right frontal cortex, $F(1,29) = 5.073$, $p = .032$, $\mu^2 = .149$. HbO was greater than HbR on all of these channels (see Figure 6). An interaction between Oxy and performance on the TC task was also observed on channel 4 over right frontal cortex, $F(1,29) = 4.627$, $p = .040$, $\mu^2 = .138$. Follow-up analyses showed that children in the high performing group showed greater

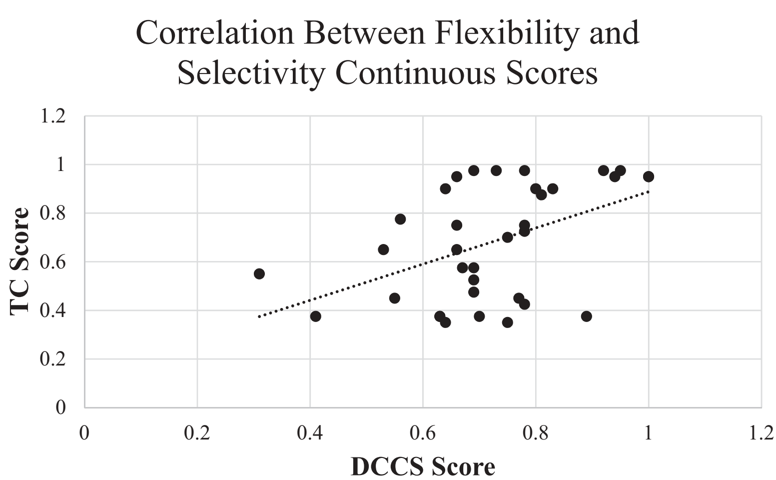


Figure 5. Correlations between continuous scores on the TC and the DCCS.

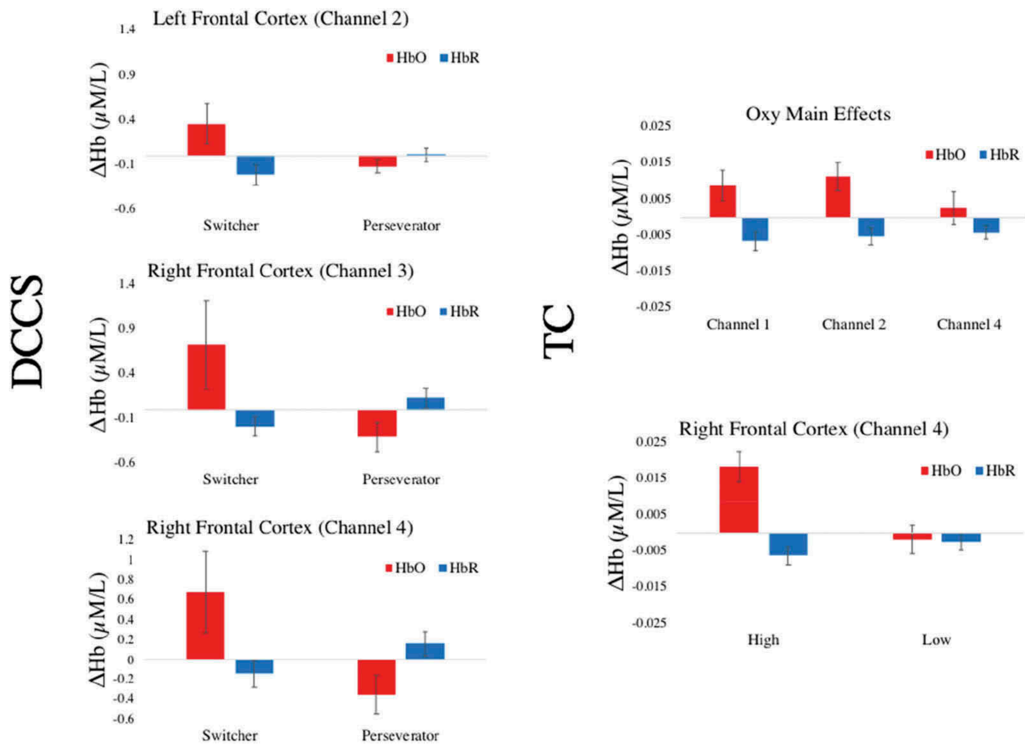


Figure 6. Changes in Hb across the DCCS task and TC task.

increases in HbO compared to children in the low performing group ($t(29) = 2.271$, $p = .031$; see Figure 6). No other effects reached significance.

Discussion

In this report, we explored the neural basis of selective and flexible dimensional attention during early childhood. First, our results indicated that successful performance on the flexible attention task is associated with stronger switching-related activation across the bilateral frontal cortex. Second, the selective attention task was associated with activation in the left frontal cortex that was unrelated to task performance. Importantly, there was convergence between the two tasks in the right frontal cortex where activation was also associated with performance on the TC task. This pattern of results suggests that children who are successful on either task showed enhanced activation in the right frontal cortex. This result suggests that a common neural mechanism underlies successful performance on flexible and selective dimensional attention tasks. This pattern of results also suggests that the left frontal cortex may serve distinct roles in flexible and selective attention. However, more work should be done to see if this generalizes across featural information or if this is a color and shape specific relationship.

These results are interesting for a number of reasons. There are fundamental differences between the demands imposed by these tasks: the DCCS task engages attention that is guided by explicit rule-based instructions to guide flexible attention. The TC task, on the other hand, requires selective attention. Further, dimensional attention in the DCCS task is explicitly instructed, whereas the dimensional attention in the TC task is implicitly guided by the configuration of stimuli. Despite these differences, we presented evidence that these forms of attention engage a common region in the right lateral frontal cortex. In previous work, we have used a dynamic neural field model to explain developmental associations in performance between these tasks (Buss & Kerr-German, 2019). The model combines object representation processes with dimensional label learning processes. As associations are strengthened between labels such as "color" and "shape" and their associated perceptual dimensions, the model can more strongly modulate object representation processes. Importantly, the connections between labels and features are bi-directional. Thus, labels can serve to guide processing of object features when directly instructed as in the DCCS task, but can also guide attention when the configuration of object features cues attention implicitly. For this reason, the model predicts that a common neural mechanism underlies successful performance across these tasks. The results presented here provide converging evidence that common neural mechanisms underlie the development of explicit and implicit, flexible, and selective dimensional attention. No other existing theories have proposed such associations in behavioral performance or neural mechanisms should exist.

The data presented here replicate previous findings that the bilateral frontal cortex is important for the development of flexible rule-use in the DCCS task (Moriguchi & Hiraki, 2011). These data also suggest that selective attention processes maybe have unique neural signatures as well. Specifically, the left frontal cortex was activated during the DCCS task only for children who switched rules; however, left frontal cortex activation was activated across all children in the TC task regardless of their level of performance. This pattern of results suggests that the left and right frontal cortex may be engaged based on different cognitive demands. It also illustrates a dissociation between activation levels in frontal cortex and performance on cognitive tasks. That is, previous research has shown that left frontal cortex activation tracks performance on tasks such that increases in activation are associated with increases in performance (Buss & Spencer, 2018); however, in this case, we observed activation that was not discriminated by task performance.

There are many important limitations to this study. Most notably is the relatively sparse measurement of neural activation based on the number of available sources and detectors. For this reason, it is possible that there were regions of cortex that were activated but went undetected by our probe. For example, previous studies have shown that activation in posterior cortical regions is also important for successful performance on the DCCS task (Buss & Spencer, 2018); however, we did not find any activated channels in the posterior cortex across either task. Our inability to detect posterior activation could be due to the sparse fNIRS probe. Further, a central hypothesis that was tested in this study was that flexible and selective dimensional attention relies upon common neural mechanisms. This was motivated by the DF model and the dimensional label learning hypothesis; however, this study did not directly measure children's understanding of dimensional labels. Ongoing work in our lab is using fNIRS probes with more extensive coverage of cortex to examine the neural basis of dimensional label comprehension and production and developmental associations with emerging dimensional attention skills. Thus, future research will need to examine the extent to which dimensional label learning creates changes in neural activation that facilitates performance on dimensional attention tasks.

Disclosure statement

No potential conflict of interest was reported by the authors.

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