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Empirical Tests of a Brain-Based Model of Executive Function Development

Sammy Perone
Washington State University

Daniel J. Plebanek
The Ohio State University

Megan G. Lorenz
University of Iowa

John P. Spencer and Larissa K. Samuelson
University of East Anglia

Executive function (EF) plays a foundational role in development. A brain-based model of EF development is probed for the experiences that strengthen EF in the dimensional change card sort task in which children sort cards by one rule and then are asked to switch to another. Three-year-olds perseverate on the first rule, failing the task, whereas 4-year-olds pass. Three predictions of the model are tested to help 3-year-olds (N = 54) pass. Experiment 1 shows that experience with shapes and the label "shape" helps children. Experiment 2 shows that experience with colors—without a label—helps children. Experiment 3 shows that experience with colors induces dimensional attention. The implications of this work for early intervention are discussed.

The emergence of executive function (EF) abilities during early childhood plays a foundational role in development. EF refers to a set of neurocognitive processes involved in goal-directed behavior (Blair & Raver, 2015; Carlson, Zelazo, & Faja, 2013; Müller & Kerns, 2015; Zelazo, 2015) that includes working memory, inhibitory control, and cognitive flexibility (Miyake et al., 2000; see also, Brydges, Fox, Reid, & Anderson, 2014; Wiebe et al., 2011). Having strong EF abilities helps children meet the demands placed on them in the home (e.g., following rules) and classroom (e.g., sitting still) and predicts outcomes across a wide array of contexts (Carlson et al., 2013; Müller & Kerns, 2015). For example, good EF abilities are associated with good academic performance (Blair & Razza, 2007), good social abilities (Clark, Prior, & Kinsella, 2002), and the rapid acquisition of new concepts (Bascandziev, Powell, Harrris, & Carey, 2016). Having poor EF abilities during early childhood can cascade into negative long-term outcomes. In fact, children with poor EF abilities are more likely to develop into adults with low socioeconomic status, have poor health, and become involved in criminal activity (Moffitt et al., 2011). Thus, there is a need for interventions that strengthen EF abilities during early childhood.

The key to successful EF interventions is transfer across contexts. Unfortunately, transfer beyond the training context has been a barrier for many cognitive intervention efforts (for reviews, see Melby-Lervåg & Hulme, 2013; Shipstead, Hicks, & Engle, 2012). For example, Redick et al. (2013) found that intensive working memory (WM) training in adults led to improvements in the practiced tasks but no transfer to other measures of cognition (e.g., WM capacity). Intervention efforts during early childhood have also yielded mixed results. For example, Blakey and Carroll (2015) showed that WM training in 4-year-old children improved performance on nontrained WM tasks, although this training did not impact performance on inhibitory control or cognitive flexibility tasks (for a similar result, see Thorell, Lindqvist, Nutley, Bohlin, & Klingberg, 2009).

At present, we have a limited understanding as to why some training experiences promote transfer

Sammy Perone and Daniel J. Plebanek contributed equally to this manuscript and serve as joint first authors; order of listing is alphabetical.

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Correspondence concerning this article should be addressed to Sammy Perone, Department of Human Development, Washington State University, 515 Johnson Tower, Pullman, WA 99164 or Larissa K. Samuelson, School of Psychology, University of East Anglia, 0.09 Lawrence Stenhouse Building, Norwich, NR4 7TJ United Kingdom. Electronic mail may be sent to sammy.perone@wsu.edu or l.samuelson@uea.ac.uk.

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to nontrained tasks and others do not. This is certainly an empirical issue as researchers probe different training regimes to see which ones promote transfer. But it is also a theoretical issue. Simmering and Perone (2013) proposed that advances in theory might offer new insights into how experience impacts cognition across contexts. In this spirit, Perone, Molitor, Buss, Spencer, and Samuelson (2015) used a theoretical model of EF development that specifies the processes by which experience is carried across contexts as a guide to enhance children's performance in the dimensional change card sort (DCCS) task.

The DCCS task is a canonical probe of early EF (Zelazo, 2006). The task is shown at the top of Figure 1, featuring a set of two-dimensional objects called "buggles." In the standard version of the DCCS task, children are asked to sort objects by one dimension (e.g., shape) during a preswitch phase before switching to the other dimension (e.g., color) in the postswitch phase. Typically, 4-year-old children readily switch the dimension by which they sort and are said to pass the task. Three-year-old children, by contrast, perseverate on the preswitch dimension and are said to fail the task.

The literature is populated with studies aiming to enhance children's performance in the DCCS task. For example, some studies have simplified the standard version of the task so that selective attention to one dimension is not required (e.g., Brace, Morton, & Munakata, 2006; Brooks, Hanauer, Padowska, & Rosman, 2003). Other studies have explicitly trained children to attend to the bidimensionality of the cards (Mack, 2007; Ramscar, Dye, Gustafson, & Klein, 2013), asked children to name the relevant dimension when they incorrectly sort cards (Espinet, Anderson, & Zelazo, 2013; see also, Kloo & Perner, 2003), or give children feedback on their sorting decisions (Van Bers, Visser, & Raijmakers, 2015). All of these studies have shed important light on how aspects of the DCCS task can be manipulated to help young children think flexibly, but they have not tackled the challenge of transfer across contexts.

Perone et al. (2015) used a dynamic neural field (DNF) model of EF proposed by Buss and Spencer (2014) to construct a set of specific experiences in a memory game that were predicted to promote transfer to the DCCS task. Results were consistent with model predictions: Children trained in a memory game context showed enhanced EF in the standard DCCS task. This was the first demonstration that experiences outside the DCCS task context can effectively impact EF in the task. The work

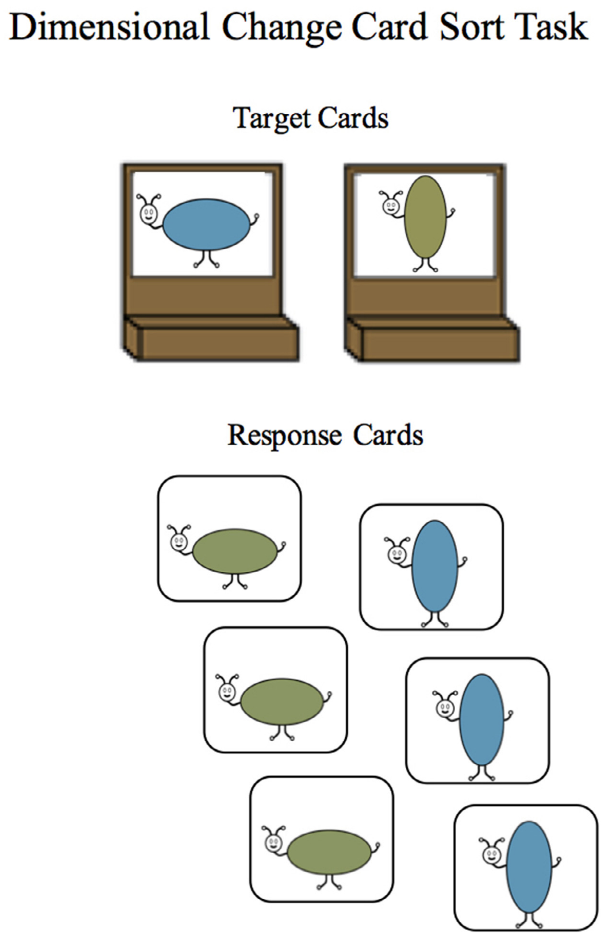

Figure 1. The dimensional change card sort task is shown. Children are asked to sort a series of response cards that match each target card by one dimension using a rule (e.g., sort by shape) before switching to a new rule (e.g., sort by shape). Four-year-old children are quite good at this, but 3-year-old children are not. [Color figure can be viewed at wileyonlinelibrary.com]

presented here builds on these efforts to better understand the mechanisms by which experience acquired in a training context impacts EF in the DCCS task. In the next section, we provide an overview of the DNF model. We then review Perone et al. (2015) who set the stage for the three novel tests of model predictions we examined in this study.

Dynamic Neural Field Model

DNF models belong to a class of neural process models. These models consist of cortical fields (neural fields) with populations of neurons tuned to continuous dimensions (e.g., color). The basic dynamics within a neural field are as follows. A stimulus excites neurons selectively tuned to its value along a dimension and local excitatory/lateral inhibitory connections within the neural field create a localized "peak" of activation. These peaks are real-time neuronal decisions about the feature values present (e.g., the specific color). Peaks, in turn, drive the formation of memory traces, which prime future decision making. For instance, the presentation of a blue stimulus might excite neurons selectively tuned to this hue value. This will create a localized peak of activation in a color field associated with actively encoding the color blue. The peak will leave a memory trace that can then facilitate the formation of a "blue" peak at a future point in time leading to, for instance, faster reaction times for blue items.

DNF models typically couple multiple cortical fields together to create neural architectures that instantiate the cognitive and neural processes hypothesized to underlie performance in particular tasks. Buss and Spencer's (2014) DNF model consists of reciprocally connected frontal and posterior systems. There is substantive evidence that strong coactivity in frontal and posterior brain regions (e.g., dorsolateral prefrontal cortex and parietal cortex) is associated with developmental change in EF from adolescence to adulthood (e.g., Crone, Wendelken, Donohue, van Leijenhorst, & Bunge, 2006; Scherf, Sweeney, & Luna, 2006; Wendelken, Munakata, Baym, Souza, & Bunge, 2012), which may result from increasing interregional connectivity (e.g., Edin, Macoveanu, Olesen, Tegner, & Klingberg, 2007; Fair et al., 2007). Little is known about the dynamics of these brain regions in EF during early childhood, a period when EF is rapidly changing (Carlson, 2005; Müller & Kerns, 2015). The DNF model is beginning to fill this gap. The model simulates children's performance in the DCCS task and has provided a theoretical account of performance across 14 variants of the task, as well as generated novel neural (Buss & Spencer, 2017) and behavioral (Buss & Spencer, 2014; Perone et al., 2015) predictions.

Figure 2 shows the DNF model. The posterior system encodes objects as colors and shapes bound to their spatial locations. Specifically, the posterior system has a spatial WM (SWM) field, shown at the top, which encodes the presence of stimuli at their spatial locations. SWM is coupled to a color WM (WM_C) and shape WM (WM_S) field, shown below SWM. These fields represent "what" is "where." The posterior system is responsible for encoding and sorting objects to the left or right. For example, Figure 2 shows hot spots (peaks) in the color and shape WM fields indicating that a short,

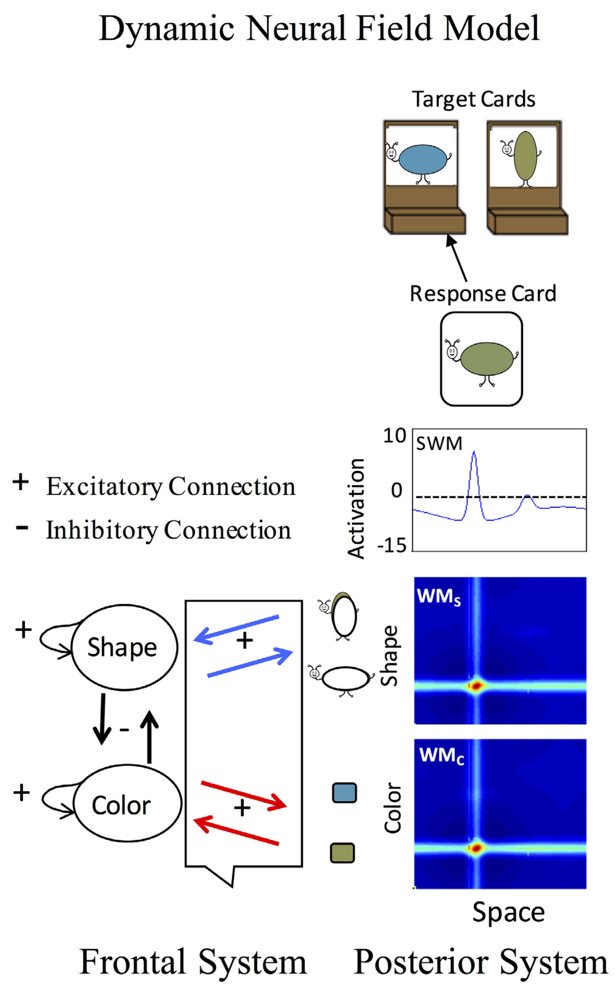

Figure 2. The dynamic neural field model is shown. The schematic highlights the model architecture and how the model performs the dimensional change card sort (DCCS) task. The model consists of coupled frontal and posterior systems. The posterior system represents "what" is "where" in color and shape working memory (WM) fields (e.g., green circles at the left). The posterior system is responsible for generating behavioral decisions to sort cards to the left or right based on the shape or color dimension. The posterior system is biased to sort by one dimension based on two influences. One influence is a top-down signal from the frontal system. For example, the shape node in the frontal system is selectively activated when the model is instructed to "sort by shape." This elevates the activity of the shape WM field, biasing the model to sort objects by their shape (e.g., to the left location, where the buggles match in shape). Another influence is the memory traces the model acquires from sorting by one dimension. For example, the model leaves memory traces for the behavioral decision to sort by shape which biases it to sort by shape at a future point in time. This is a key influence in the model's account of 3-year-old children's perseveration on the preswitch rule in the DCCS task. [Color figure can be viewed at wileyonlinelibrary.com]

green buggle is about to be sorted to the left location. Each time the shape and color WM fields form a peak, they leave memory traces in layers MT_S

and MT_C, respectively. The memory traces strengthen the response of the WM fields to previously sorted objects at the location they were sorted to. This biases the model to continue sorting the way it has in the past. These memory traces are a key source of 3-year-old children's perseveration in the DCCS task.

The frontal system consists of nodes tuned to the labels "color" and "shape." These nodes respond to the experimenter's instruction to "sort by shape" or "sort by color" and compete in a winner-take-all fashion. The winner implements a form of dimensional attention in the posterior system by selectively boosting the responsivity of the associated WM field. The shape and color nodes also have associated memory trace layers, MT_{i_shape} and MT_{i_color}, that strengthen their response to previously presented labels.

How does the DNF model perform the DCCS task? The model is instructed to sort by a dimension, for example, "sort by shape" during the preswitch phase. This activates the shape node, which in turn boosts the shape WM field. At the moment captured in Figure 2, the model has been presented with a card depicting a short, green buggle, and it has formed a peak at the left location in the shape and color WM fields. This leads the model to sort the object to the left location where the short buggles match. Like children, the model sorts six cards during the preswitch phase. In this example, this leads to the accumulation of strong memory traces for sorting short buggles to the left and tall buggles to the right.

When the postswitch phase begins, the model is instructed to sort by color. This selectively activates the color node in the frontal system, which, in turn, boosts the color WM field in the posterior system. When the strength of the connection weights between the frontal and posterior systems are relatively weak, this top-down signal to engage the color dimension is not very strong, and it cannot overcome the strong memory traces in the posterior system for sorting by shape. The model perseverates on the preswitch dimension, shape in this example, like 3-year-old children. When the strength of the connections between the frontal and posterior systems is relatively strong, the top-down signal can overcome the strong memory traces for sorting by shape, and the model sorts correctly, like 4-year-old children (for additional details, see Buss & Spencer, 2014; Perone et al., 2015). Thus, the strength of connections between the frontal and posterior systems in the DNF model is a key source of developmental change in children's performance in the DCCS task. Perone et al. (2015) probed the specific experiences that might strengthen how strongly these systems interact and, in turn, children's EF. We provide a brief review of this work next.

Targeting Frontal–Posterior Connectivity: Review of Perone et al. (2015)

The bidirectional connectivity of the frontal and posterior systems in the DNF model allows for two influences on performance in the DCCS task: (a) top-down influence from the labels can bias activation in the WM fields, and (b) activation in the WM fields can exert a bottom-up influence on the label nodes, such as when strong activity in the color WM field in the posterior system boosts the color node. Perone et al. (2015) gave the DNF model experiences that targeted both influences to strengthen the interactivity between the two systems. They provided the posterior system with experience in the form of memory traces for five colors, and they boosted the color node via repeatedly presenting the label "color." This experience increased the strength with which the frontal and posterior systems associated with the color dimension interacted, enabling the model to strongly engage the color dimension during the postswitch phase of the DCCS task. Consequently, the model overcame the memory traces associated with sorting by shape during the preswitch phase, and the model passed the DCCS task.

The memory traces associated with the five colors raise the baseline activity level of the units within the color WM field in the posterior system, and the memory traces associated with the label "color" raise the baseline activity of the color node in the frontal system. In doing so, the memory traces move local activation closer to the threshold at which peaks form, allowing subthreshold activation in the frontal and posterior systems to have more of an impact on each other. In this way, memory traces increase the effective strength with which the frontal and posterior systems project to each other. We refer to this as *effective* connectivity. This differs from the strength of the connection weights between the frontal and posterior systems. These connection weights are multiplied by the current activation to collectively determine how strongly activation in one system (e.g., frontal) influences activity in the other system (e.g., posterior). The strength of these connection weights are what Buss and Spencer (2014) proposed increase over development (discussed earlier) and are thus held constant in the present work.

To test the prediction of the DNF model, Perone et al. asked 3-year-old children to play a memory game in which they searched for matching pairs of the same colors presented to the model (Colors 1, 6, 10, 13, and 18; see Figure 3). Children also heard the label "color" repeatedly as they searched for matches. Children then participated in the DCCS task and were asked to sort by shape in the preswitch phase and color in the postswitch phase. Three-year-old children, like the model, passed the DCCS task.

Interestingly, Perone et al. (2015) found that children failed to switch from color to shape after playing a memory game with shapes (Shapes 3, 8, 12, 15, and 20; see Figure 3). Why does experience with color but not shape transfer to the DCCS task? Perone et al. proposed that the buggle shapes used in the experiment were less distinct because the shapes were minor variations of a single category (i.e., circle). To test this, they constructed a simplified memory game model and simulated learning about colors and shapes that were more or less

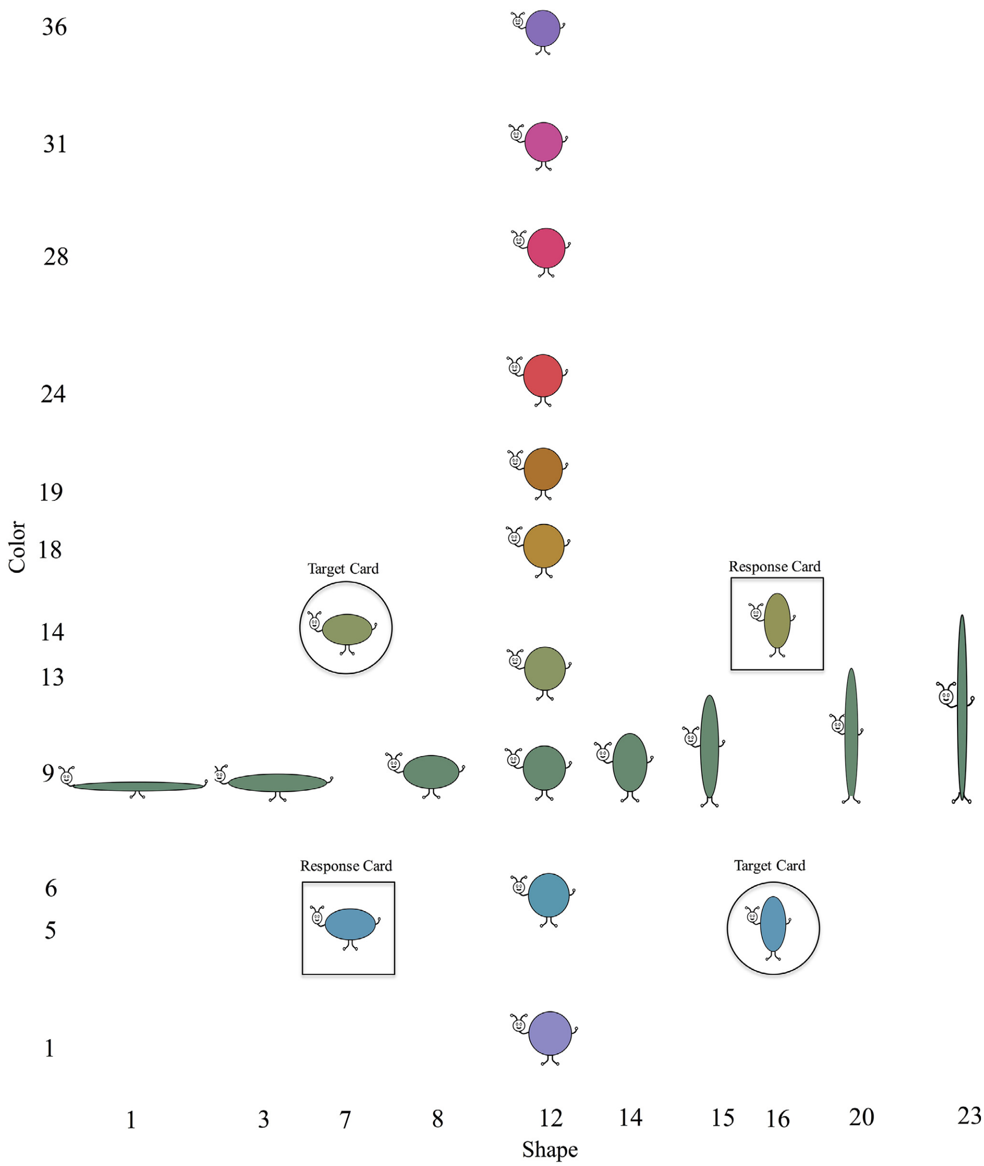

Figure 3. The buggle stimulus set is shown. Buggles consist of one value from continuous color (hue) and a continuous shape (aspect ratio) dimensions. The buggles surrounded by circles and squares show the stimuli used as target and response cards in the dimensional change card sort task. The remaining color and shape values shown highlight the stimuli used across Experiments 1–3. [Color figure can be viewed at wileyonlinelibrary.com]

discriminable (i.e., closer or farther along the represented dimension). When the features were close together, they interfered with one another, leading to less robust decisions (peaks) and weaker memory traces. When these weaker memory traces were carried forward into the DCCS model, the model failed to switch from color to shape.

Perone et al. demonstrated that the DNF model is a useful tool to probe how specific experiences influence transfer in the DCCS task. Here, we build on this work, using the same simulation approach to generate and test three novel predictions of the DNF model. The first prediction is that experience with more distinct shapes in a memory game will transfer to the DCCS task, helping 3-year-old children succeed. The second prediction is that extensive bottom-up experience is sufficient to generate transfer to the DCCS task, even without an associated label. The third prediction is that the similarity of the features between the memory game and the DCCS task is not critical—as long as strong memories are created in the memory game, even very dissimilar colors are sufficient to induce transfer.

Experiment 1

Experiment 1 tested the novel prediction of the DNF model that extra experience learning about more distinctive shapes than those used by Perone et al. (2015) will help 3-year-old children flexibly switch from sorting by color to sorting by shape in the DCCS task. The simulation method used to generate this prediction is described next, followed by the empirical test.

Simulations

The simulation method involved the same two-step process described in Perone et al. (2015). The first step was to probe the memory game model used by Perone et al. to examine what experiences would yield strong memories. Figure 4A shows the memory game model. The model consists of a one-dimensional WM field (WM_S) with neurons selectively tuned to shape and an associated memory trace layer (MT_{S_1D}). At the top are the five close shapes (Shapes 3, 8, 12, 15, and 20; Figure 3) to which children in Perone et al. were exposed. The

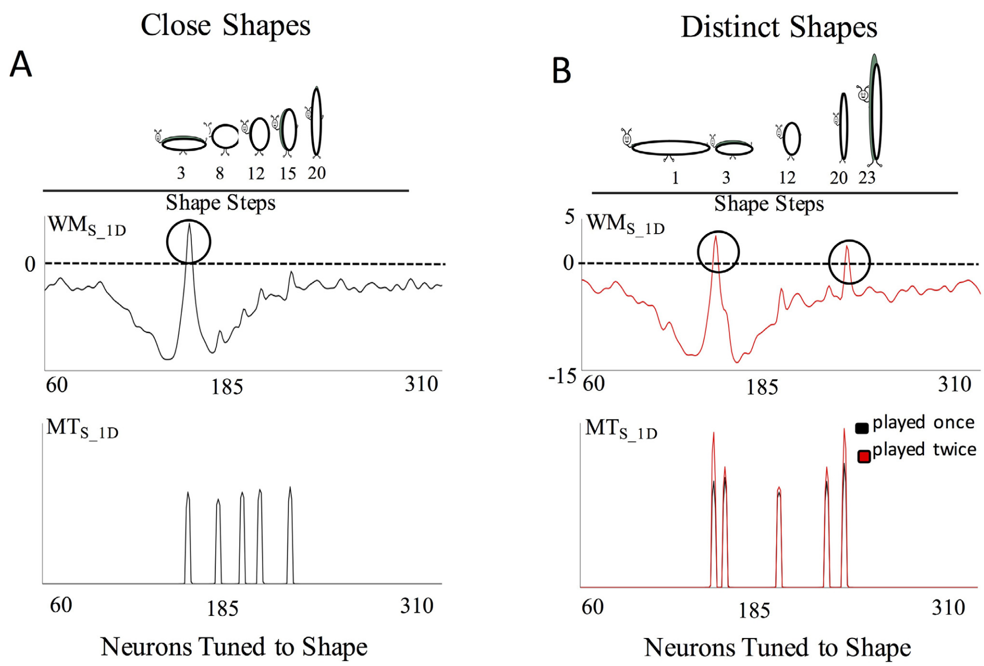

Figure 4. The memory game model from Perone et al. (2015) is shown. The figure highlights the shape memory game for close (A) and more distinct (B) shapes. The model consists of a shape working memory (WM) field (top) and associated memory trace layer (bottom). (A) A snapshot of the model learning about a collection of highly similar shapes. The WM field is remembering Shape 3, which interferes with WM for highly similar shapes (e.g., 8 and 12). This leads to the accumulation of relatively weak memory traces. (B) A snapshot of the model learning about a collection of more distinct shapes. The WM field is remembering Shape 3, which is sufficiently different from nearby shapes (e.g., 20) that it can simultaneously maintain multiple items (i.e., reduced interference relative to close shapes). This led to strong memory traces when the memory game was played twice (red lines) relative to only once (black lines). [Color figure can be viewed at wileyonlinelibrary.com]

model was presented with the five shapes in a random order across a series of 60 exposure trials, which mimics the memory game that children play in which they repeatedly flip over cards, look at a shape, and seek a match (see Method). Batches of 50 simulations were conducted to provide a robust estimate of learning. At the moment captured in 4A, the model has a localized peak associated with remembering Shape 3. The broad inhibitory trough surrounding the peak effectively “knocks out” nearby items (e.g., Shapes 8, 12, and 15) that were previously in WM. Over the course of learning, this interference leads to relatively weak memory traces associated with the five shapes (see bottom panel in Figure 4A).

Can we strengthen the memories for the shapes by spreading them out, thereby reducing interference? We tested this possibility by exposing the model to Shapes 1, 3, 12, 20, and 23 (Figure 3). We probed the memory game model after playing the memory game with these more distinct shapes once (60 exposures) and twice (120 exposures) to explore whether extra exposure would lead to increasingly robust memories for the shapes. The results are shown in Figure 4B. At the moment captured, the model is being exposed to Shape 3. Notice that the model is also maintaining Shape 20 in WM. This happens because the WM peaks associated with Shapes 3 and 20 are relatively far apart, which reduces the likelihood that the inhibitory troughs associated with one WM peak will “knock out” the other. Maintaining multiple items in WM helped the model form strong memory traces. The memory traces were stronger when the memory game was played twice (red line) than once (black line).

The simulations of the memory game set up the second step in our simulation method. Here, we imported the memory traces from the “memory game” simulations into Buss and Spencer’s (2014) DNF model, effectively asking whether this prior experience would impact DCCS performance. The memory traces were imported as ridges of input across the spatial dimension, generalizing the experience with the five distinct shapes across all locations. The memory trace layer associated with the shape node (MT_{i_shape}) in the frontal system was also initialized with a memory for the label “shape” to capture experience with the label “shape” during the memory game that children play (see Method). The model was situated in the DCCS task and instructed to sort by color during the preswitch phase and by shape during the postswitch phase. Batches of 100 simulations were run to provide an estimate of the model’s overall performance in the presence of simulation-to-simulation variation.

Figure 5 shows the simulation results. The rate at which the DNF model passed the DCCS task when given robust experience with distinct shapes and the label “shape” was greater than when the model performed under the standard conditions (compare distinct shapes to standard in Figure 5A). The memory game experience strengthened the effective frontal–posterior connectivity associated with the shape dimension. In particular, the strength of the effective connection from the frontal-to-posterior system (see distinct shapes in Figure 5B) and back from the posterior system to the frontal system (see distinct shapes in Figure 5C) was stronger for shape (red bars) than for color (blue bars). The effective connectivity associated with the shape dimension was much greater than under the standard conditions (see standard in Figures 5B and 5C). This enabled the DNF model to strongly engage the shape dimension during the postswitch phase and overcome the strong memory traces associated with sorting by color during the preswitch phase. Note that the measures of effective connectivity from the frontal-to-posterior system shown in Figure 5 were the mean strengths of the projections from the color and shape nodes to the color and shape WM fields, respectively, across the pre- and postswitch phases of the DCCS task. The reverse projections were used as the measure of effective connectivity from the posterior-to-frontal system. Additional simulation details and model parameters can be found in Appendix S1.

Empirical Test

The DNF model predicts that a shape memory game with distinct shapes played twice will help 3-year-old children switch from sorting by color to sorting by shape in the DCCS task. In the following, we describe the empirical test of this prediction. Note that, if successful, this would extend the findings from Perone et al. (2015), showing that experience in a memory game can influence DCCS performance regardless of whether children search for memory matches based on color or shape.

Method

Participants

Eighteen 3-year-old children (M = 43.4 months, range = 39–47 months, 8 girls) participated in

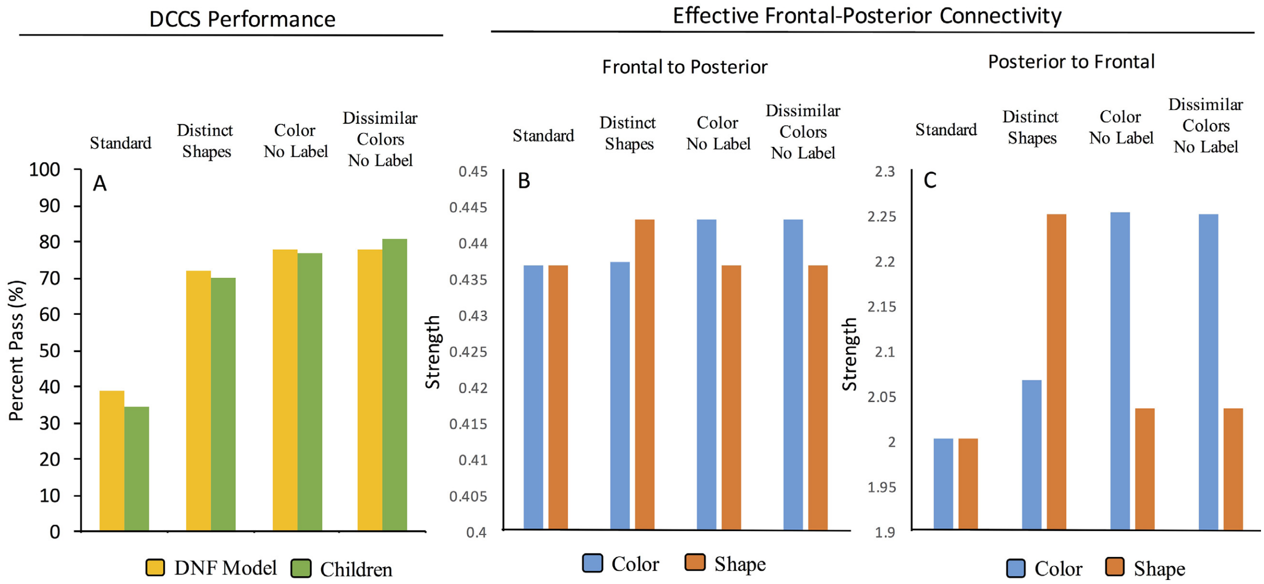

Figure 5. Children's and the model's performance in the dimensional change card sort (DCCS) task (A) as well as the strength of effective frontal-to-posterior (B) and effective posterior-to-frontal (C) connectivity across all conditions. Children's and the model's performance under the standard condition was poor (left side of A), which improved after playing a memory game with distinct shapes, colors with no "color" label, or colors dissimilar to those used in the DCCS task. These improvements were attributable to stronger effective connectivity with the dimension children, and the model was exposed to in the memory game. For example, after playing the memory game with distinct shapes, the effective frontal-to-posterior (B) and effective posterior-to-frontal (C) connectivity was stronger for the shape dimension than under the standard condition (compare bars under standard and distinct shapes). This stronger connectivity enabled the model to more strongly engage the postswitch dimension (shape in this example) and sort correctly in the DCCS task. [Color figure can be viewed at wileyonlinelibrary.com]

Experiment 1. In all experiments reported here, children were recruited from birth records and local child-care facilities. Children were predominately Caucasian and from middle-class families and received a small prize for their participation. The performance of the participants in the present investigation will be compared with that of 18 participants from Perone et al. (2015) who performed the DCCS task under the standard conditions alone. Those children were also drawn from the same community as the children in the present investigation and were predominately Caucasian, from middle-class families, and of similar age to children in all experiments reported here (M = 41.20 months, range = 37–47 months, 10 girls). For all experiments, data were collected between September 2011 and October 2015.

Stimuli

The stimuli were "buggles" and are shown in Figure 3 (Perone & Spencer, 2014). Buggles consist of a value along a continuous color (hue) and shape (aspect ratio) dimension. For example, buggle s5c5 is an object with the fifth shape on the shape dimension (s5) and fifth color on the color dimension (c5). The color dimension consists of 36 equidistant colors sampled from a 360° continuous color space (CIE*Lab, 1976). The shape dimension is composed of 23 equidistant steps defined by a proportional change in height and width, holding total area constant. Note that we stretched the shape dimension relative to Perone et al. (2015) from 18 steps to 23 steps to test the novel prediction of the DNF model. This involved adding two metric steps to the short (left) side of the dimension and three metric steps to the tall (right) side of the dimension. We relabeled the shapes such that Shapes 3 and 8 were Shapes 1 and 6 in Perone et al. The shapes used in the shape memory game were the same as the shapes that were presented to the DNF model (Shapes 1, 3, 12, 20, and 23). All shapes shared the same color (Color 10).

We counterbalanced the use of two sets of cards for the DCCS task that involved the same color and shape values as the DNF model. The target and response cards are highlighted in Figure 3. The first set used buggles s7c5 and s16c14 as target cards and s7c14 and s16c5 as response cards. The second set used s7c14 and s16c5 as target cards and s7c5 and s16c14 as response cards. Children sorted the response cards into wooden trays.

Design and Procedure

Children first participated in the memory game. The experimenter and child sat at a table with the memory game cards spread out face up and within reaching distance of the child. The experimenter familiarized the child with each matching pair of cards by saying, "Look! These buggles are the same shape!" The experimenter then flipped over all the cards and scrambled them. The experimenter showed the child how to play the game by turning over two nonmatching cards and said, "These two aren't the same shape." The experimenter flipped the cards back over so they were face down and the child and experimenter took turns looking for matches. If the pair matched, the cards were removed from the game. If the pair was not a match, the experimenter said, "These aren't the same shape" and flipped the cards back over. Each child was required to make four of the five matches during the game. To ensure this, the experimenter selected nonmatching pairs for the majority of the task. After the five matches were found, the memory game was repeated one more time. Immediately following the second memory game, the experimenter administered the DCCS task.

The DCCS task followed Zelazo's (2006) protocol. All children were asked to sort by color during the preswitch phase and shape during the postswitch phase. The experimenter began by introducing the target cards and stated the preswitch rule to sort by color (i.e., "We're going to play the color game. In the color game, all of the blue buggles go here and all of the green buggles go here."). The experimenter demonstrated how to sort by the preswitch dimension and ensured that the child could do the same. Children were asked to sort the six cards by color. If the child sorted incorrectly, the experimenter restated the sorting rule. After the preswitch phase, the postswitch phase began. The experimenter told the child the postswitch rule to sort by shape but did not demonstrate how to sort by the postswitch dimension. Children were asked to sort six cards by the new rule during the postswitch phase. As in the preswitch phase, the experimenter restated the sorting rule if the child sorted incorrectly.

Results

Figure 5A shows the results (see green bar, distinct shapes). To be included in the analyses, children were required to sort 5 of 6 cards correctly during the preswitch phase (Zelazo, 2006). All children met this criterion. In order to pass the DCCS task, children were required to correctly sort at least five cards in the postswitch phase of the task. Thirteen of 18 (72.2%) children passed (binomial, $p < .05$). Perone et al. (2015) found that 7 of 18 (38.9%) children passed under the standard, no memory game, conditions (shown in Figure 5A for comparison). This is a good baseline comparison of children's performance because those children sorted cards using the same stimuli used here. A chi-square analysis showed that significantly more children in Experiment 1 passed than under the standard conditions from Perone et al., $\chi^2(1, N = 36) = 4.05$, $p = .0442$. Three-year-old children successfully switched from sorting by color to sorting by shape in the DCCS task after playing a memory game with distinct shapes, much like 4-year-old children perform under the standard conditions. This contrasts with data from a second set of 3-year-old children from Perone et al. (2015) who played a memory game with close shapes prior to the DCCS task. Only 8 of 18 (44.4%) of those children successfully switched from sorting by color to sorting by shape.

Discussion

The results of Experiment 1 are consistent with the prediction of the DNF model that exposure to distinct shapes induces flexible switching from color to shape in 3-year-old children. This explicitly tested Perone et al.'s (2015) hypothesis that the buggle shapes are represented in a more compressed space relative to the colors. Simulations of the memory game model indicate that learning about close (similar) shapes results in interference and ultimately weak memory traces for those shapes. Spreading the shapes out helps reduce this interference, leading to strong memories for the distinctive shapes after playing the memory game. This, in turn, strengthened the effective frontal–posterior connectivity associated with the shape dimension in the DNF model and enabled it to strongly engage the shape dimension during the postswitch phase of the DCCS task. Other studies have also shown that similar values on a dimension can create interference in children's performance in the DCCS task. For example, Fisher (2011) found that 3-year-old children failed to switch from sorting by a dimension with distinct features (e.g., flower and star) to a dimension with similar features (e.g., pink and red). Children passed when switching from a dimension with similar features to a dimension with distinct features (for simulations of these effects, see Buss & Spencer, 2014).

Experiment 2 tests whether the bottom-up influence of features alone, without labels, is sufficient to enhance children's performance in the DCCS task. Experiment 3 tests whether the memory game transfers to the DCCS task at the level of dimensions or if it is limited to values that are similar to values experienced in the memory game. These tests are conducted using only the color dimension in the memory game because the color dimension is much larger than the shape dimension. This makes it more amenable to strong tests of the theoretical predictions of the DNF model.

Experiment 2

Perone et al. (2015) found that providing children experience with buggles sampled from the color dimension and the label "color" during the memory game helped children switch from sorting by shape to sorting by color in the DCCS task. Here, we asked whether experience with the colors alone provided to the posterior system—without experience with the label "color" provided to the frontal system—was sufficient to strengthen the effective frontal–posterior connectivity associated with the color dimension and facilitate performance in the DCCS task.

Model Simulations

The DNF model was provided experience with five colors (Colors 1, 6, 10, 13, and 18; Figure 3) in the form of memory traces as was done in Perone et al. (2015) and Experiment 1 for shapes. The key manipulation was that the frontal system was *not* initialized with a memory for the "color" label.

Figure 5 shows the simulation results. The DNF model passed the DCCS task at rates greater than when it performed under the standard conditions (compare color no label to standard in Figure 5A). Bottom-up experience with colors increased the strength of the effective frontal–posterior connectivity for the color dimension. In particular, the strength of effective connectivity from the frontal-to-posterior system (see color no label in Figure 5B) and back from the posterior system to the frontal system (see color no label in Figure 5C) was stronger for color (blue bars) than for shape (red bars). This enabled the DNF model to strongly engage the color dimension during the postswitch phase and overcome the strong memory traces associated with sorting by shape during the preswitch phase. Importantly, the DNF model sorted correctly during the preswitch phase when asked to sort by shape under the standard conditions and after experience with colors from the color memory game. Thus, the memory game did not impact the model's preswitch performance. Moreover, the strength of memory traces associated with sorting by shape during the preswitch phase was similar under the standard condition and after experience with colors from the color memory game. Thus, the model's improved performance in the postswitch phase after experience with colors was not attributable to the formation of a weaker bias in the preswitch phase.

Empirical Test

The role of labels in children's performance in the DCCS task is relatively unexplored. There is some evidence that familiar labels can *negatively* impact children's performance in the task. In particular, Yerys and Munakata (2006) proposed that the familiarity of the labels typically used in the DCCS task helps generate strong memories during the preswitch phase and, consequently, perseveration on the preswitch dimension during the postswitch trials. Indeed, they found that younger children passed the DCCS task when *less informative* labels were provided, such as "sorting game" instead of the familiar "shape" and "color." The model simulations fit with the idea that dimensional labels can generate strong memories. The model suggests that this is due to dynamic interactions between the frontal and posterior systems. In particular, the strong memories associated with color from the memory game in the posterior system send strong activity to the "color" node in the frontal system, which leads the "color" node to send strong activity back. This primes the model to engage the color dimension more strongly than the shape dimension in the postswitch phase.

Method

Participants

Twenty-five 3-year-old children (M = 42.5 months, range = 36–46 months, 13 girls) participated in Experiment 2. Two children were excluded for failing the preswitch phase and five children were excluded due to experimenter error.

Stimuli, Design, and Procedure

The stimuli, design, and procedure were identical to Perone et al. (2015) except that children did not hear the dimensional label "color" during the color memory game. Instead, the experimenter simply said, "Look! These are the same" when familiarizing children to the pairs of cards and "These aren't the same" when no match was found. The colors used in the memory game were 1, 6, 10, 13, and 18 and all shared Shape 12 (Figure 3). Children were asked to sort by shape in the preswitch phase and by color in the postswitch phase during the DCCS task. All other procedural details were identical to Experiment 1. Note, in particular, that the DCCS task followed the standard procedure, including the use of the words "color" and "shape" to refer to the dimensions.

Results

Figure 5A shows the results (see green bar, color no label). When children played the color memory game without the label "color," 14 of 18 (77.8%) children passed the DCCS task (binomial, $p < .05$). As in Experiment 1, we compared children's performance here to 3-year-old children's performance under the standard conditions from Perone et al. (2015). Only 7 of 18 (39.8%) children in that study passed the DCCS task under the standard conditions, which a chi-square test revealed was significantly fewer than in Experiment 2, $\chi^2(1, N = 36) = 5.60$, $p = .018$. As in Perone et al., children passed the DCCS task after playing the color memory game. These results indicate that experience with the postswitch dimension alone is sufficient to help children think flexibly in the DCCS task.

Discussion

The results of Experiment 2 are consistent with the DNF model prediction that the color memory game without the dimensional label "color" facilitates children's performance in the DCCS task. The simulation results showed that this is attributable to the interactivity of the frontal and posterior systems —the dynamic back-and-forth between the "color" node in the frontal system and the color WM field in the posterior system strengthens the effective connectivity associated with the color dimension. This raises the intriguing possibility that one can enter the frontal–posterior loop in a bottom-up fashion for the purposes of early EF interventions. However, it is unclear whether this bottom-up experience is enhancing attention that is anchored to a limited range of the dimension or at the level of the entire dimension, which would make the experience a more powerful transfer tool. We explore this issue in Experiment 3.

Experiment 3

In all of the examples of the memory game here and in Perone et al. (2015), the features used in the memory game were chosen to be similar to those presented in the DCCS task. This raises a critical question: Does the memory game transfer to the DCCS task at the dimensional level or is transfer limited to a range of features along a dimension? We test this possibility in a *dissimilar color memory game.* If the color memory game transfers to the DCCS task at the dimensional level, we should expect children to pass the DCCS even when they sort response cards with colors that are dissimilar to those present in the memory game. We explicitly tested this possibility in the DNF model by simulating its performance with one set of colors in the DCCS task (blues and greens) after being provided experience with very different colors (reds and oranges).

Simulations

The simulation method was identical to Experiment 2 with one exception. The memory trace layer associated with the color WM field was initialized with Colors 19, 24, 28, 31, and 36 (Figure 3). Note that these colors have the same range and distribution of colors as the color memory game from Experiment 2 but are sampled from a different section of the color dimension than those sorted in the DCCS task.

Figure 5 shows the simulation results. The DNF model passed the DCCS task at rates greater than when the model performs under the standard conditions (compare standard to dissimilar colors/no label in Figure 5A). Experience with colors that were dissimilar to those used in the DCCS task still facilitated the model's flexible rule use. The reason is that the color memories provided to the posterior system selectively strengthen the connection from the color WM field to the "color" node in the frontal system (see dissimilar colors/no label in Figure 5B), which in turn selectively boosts the *entire* color WM field in the posterior system (see dissimilar colors/no label in Figure 5C). This enabled the DNF model to strongly engage the dimension during the postswitch phase and overcome the strong memory traces associated with sorting by shape during the preswitch phase.

Empirical Test

The dissimilar color simulations suggest that prior experiences with the postswitch dimension can boost performance in the DCCS even if the values experienced are very different from those used in the DCCS. The DNF model prediction is consistent with an early study on dimensional attention by Tighe and Tighe (1969). They asked children in the first grade to play a game in which they judged whether different sized cylinders matched an exemplary cylinder (e.g., Sizes 4, 5, and 7 in.). This experience helped the children represent relations in a transposition task completed later with very different sized cylinders (e.g., Sizes 10 and 15 in.). We describe our empirical test of the model's prediction later.

Method

Participants

Twenty-eight 3-year-old children (M = 43 months, range = 38–47 months, 13 girls) participated in this experiment. One child was excluded from the analyses for fussiness, five children failed the preswitch phase, and four children were excluded due to experimenter error. Children and parents were recruited and compensated in the same manner as in Experiments 1 and 2.

Stimuli, Design, and Procedure

The stimuli, design, and procedure were identical to Experiment 2 except that the colors used during the dissimilar color memory game were selected from the other side of the color dimension (reds and oranges) relative to the colors used in the DCCS task (blues and greens). The colors used were, however, the same as were presented to the DNF model and had the same distribution as in Experiment 2. The colors were 19, 24, 28, 31, and 36 (Figure 3) and shared Shape 12.

Results

Children's performance in the DCCS is shown in Figure 5A (see green bars, dissimilar no label). After playing the dissimilar color memory game, 14 of 18 (77.8%) passed the DCCS task (binomial, $p < .05$). As in Experiments 1 and 2, we compared children's performance here with 3-year-old children's performance from Perone et al. (2015). Only 7 of 18 (39.8%) children there passed the DCCS task under the standard conditions using the same stimuli used here, which a chi-square test revealed was significantly fewer than in Experiment 3, $\chi^2(1, N = 36) = 5.60$, $p = .018$. These results indicate that experience with colors in the memory game context transfers at the dimensional level to the DCCS task.

Discussion

Previous variants of the color memory game left open the question of how experience over the color dimension influences attention across contexts. The results of Experiment 3 indicate that the color memory game induces dimensional attention rather than attention to a more localized region of the color dimension. Our findings are consistent with recent work by Perry and Samuelson (2013; see also Perry 2013) who demonstrated that dimensional attention can be trained across task contexts. Perry and Samuelson classified children as either dimensional or holistic attenders in a triad classification task with stimuli that varied along size and brightness dimensions. After classification, children learned to sort stimuli into categories based on one of the dimensions. After training, children participated in a posttest triad task. Some of the children who were initially holistic attenders now attended dimensionally. These results parallel our findings as they demonstrate that experience with dimensions can be a powerful tool to shift attention even across task contexts.

General Discussion

The demand for cognitive interventions across the life span is increasing. A central challenge facing such intervention efforts is the transfer problem: Often, cognitive training does not generalize beyond the training context (for a review, see Shipstead et al., 2012). Buss and Spencer's (2014) DNF model has shown promise in tackling the transfer challenge. The model simulates children's performance in a canonical probe of early EF, the DCCS task. Developmental change in EF in the model is due to increasingly strong connection weights between the frontal and posterior systems. We have targeted this connectivity as an avenue to enhance 3-year-old children's performance in the DCCS task under conditions in which they typically perform poorly. For instance, we provided children experience with color in a memory game context and showed that this helped them flexibly switch attention to color in the DCCS task. In the DNF model, this experience strengthens the effective frontal–posterior connectivity associated with color and enables the model to more strongly engage and, consequently, switch attention to color in the DCCS task. The link between strengthening effective frontal–posterior connectivity and improved EF here is consistent with previous cognitive training intervention efforts with older adults. For example, Anguera et al. (2013) found that multitasking training led to increased frontal–posterior connectivity (coherence) in the theta (4–8 Hz) frequency band, a range of neural oscillations associated with EF. The degree to which connectivity increased was associated with improved performance on measures of attention.

One question of great importance is whether the laboratory-based interventions showcased here provide a window into the mechanisms that drive developmental change in EF. Answering this question is important not only for advancing our theoretical understanding of EF development but also for the practical aspects of developing effective early EF interventions. The experience in the memory game increases the effective frontal–posterior connectivity associated with a dimension. An open question is whether or not experience over a dimension drives EF development via incremental strengthening of effective frontal–posterior connectivity or whether the connection weights between the frontal and posterior systems must also change. Perone and Spencer (2014; see also Perone & Spencer, 2013) provided some evidence that the accumulation of real-time experience with features across a dimension over a long-time scale can create developmental change in neurocognitive (e.g., working memory) and behavioral (e.g., gaze) dynamics. This is similar to prior work in early word learning. In particular, Smith and Samuelson and their colleagues have shown that providing children experience with categories organized by similarity in shape can induce dimensional attention to shape when learning new names, facilitating vocabulary development (Samuelson, 2002; Smith, Jones, Landau, Gershkoff-Stowe, & Samuelson, 2002). Similarly, providing repeated experience with objects and labels to Buss and Spencer's (2014) DNF model should strengthen the effective frontal–posterior connectivity associated with many dimensions. This, in turn, should enable the model to more strongly engage those dimensions to selectively control attention in tasks such as the DCCS. Note that this is an empirically testable hypothesis. For instance, 3-year-old children could be trained along multiple dimensions for several months after which they should show an increased ability to switch attention in variants of the DCCS that involve those dimensions relative to nontrained controls. Such empirical inquires will help us resolve questions about the underlying mechanisms at work in EF development.

Buss and Spencer's (2014) DNF model has shed light on EF development, but how far can a computational model take us? The DNF model has captured children's performance across an unprecedented number of conditions of the DCCS task (see Buss & Spencer, 2014). Explaining existing data is only one aspect of theory, however. The gold standard for theory is the capacity to generate novel predictions. The DNF model is doing a good job on this front as well, as illustrated here at the behavioral level (see also Buss & Spencer, 2014; Perone et al., 2015) and by Buss and Spencer (2017) at the neural level. This previous research exemplifies a strong theory–experiment dialog. For example, Perone et al. (2015) observed that the shape memory game played with similar shapes did not help children switch attention to shape in the DCCS task. This prompted the authors to test whether the high similarity of their shapes might lead to interference during learning in the shape memory game. This, in turn, led to the novel prediction, tested here, that playing the shape memory game twice with more distinct shapes should help children form strong memories and facilitate switching attention to shape in the DCCS task.

Furthermore, the predictions tested here and in Perone et al. (2015) are unique to the DNF model. Consider Morton and Munakata's (2002) connectionist model of early EF development, which has also provided an account of children's performance in the DCCS task. That model consists of nodes associated with features sampled from a dimension (e.g., blue, star, red, circle) and nodes for each label. The model forms a strong latent (long-term) memory for the features and labels used during the preswitch phase. This strong latent memory leads a 3-year-old version of the model to perseverate during the postswitch phase because it overpowers a weaker active (working memory) representation for the features and labels used during the postswitch phase. The DNF model's account of children's performance in the DCCS task is similar. However, a unique feature of the DNF model is that its experience with features is distributed over a continuous dimension. Consequently, experience with some features—as in the memory game—can impact how it makes decisions about other features that it has not been exposed to previously—as in the DCCS task. The connectionist model, by contrast, processes information at the featural—not the dimensional—level. Thus, it is unclear how experience with one set of features might impact its performance with another set of features (for additional model comparisons, see Buss & Spencer, 2014).

This feature of the DNF model has also yielded novel insights into how values sampled from a dimension can impact children's performance in the DCCS task. For example, Fisher (2011) showed that children's performance in the DCCS task is affected by the details of the dimensions they are asked to sort by. In particular, whether or not children can flexibly switch attention to a dimension depends on the values sampled from the postswitch dimension. If those values are relatively distinct, children pass; if those values are highly similar, children fail. Buss and Spencer (2014) showed in the DNF model that failing during the postswitch phase when values are highly similar results from competition in the postswitch neural field as it tries to form peaks at very similar locations, such as a peak for a pink item and a peak for a red item. This interference in the postswitch dimension, in turn, leads the model to fall back on its bias to sort by the preswitch dimension. A different type of interference was reported by Perone et al. (2015). In that report, the memory game model had difficulty maintaining WM peaks for highly similar shapes because they were represented by nearby locations in the neural field. Interference in the close memory game led to the formation of weaker memory traces for the close shapes. When these weak shape memory traces were carried forward to the DCCS task, they were too weak to help the model strongly engage the shape dimension in the postswitch phase of the DCCS task. Thus, the model suggests that failure during the postswitch phase of Fisher's task resulted from the challenge of making decisions about metrically similar shapes in the context of competing biases toward color, whereas failure in the memory game task results from an inability to engage the postswitch dimension because of weak memory traces.

The present investigation also raises questions about the role of dimensional labels in EF. There is some evidence that labels play an important role in dimensional attention. For example, Yerys and Munakata (2006) showed that children's experience with labels in the lab builds on their developmental history with those labels. For instance, they showed that children flexibly switch rules in the DCCS task when less typical or no labels are provided to them during the preswitch phase of the DCCS task. Very little is known about developmental change in how children learn about dimensional labels and labels for values along a dimension. There is some research showing substantial development in children's mapping between color labels and color boundaries between 3 and 5 years of age (Saji, Asano, Oishi, & Imai, 2015; Wagner, Dobkins, & Barner, 2013). For example, with age there is less overlap between the color values (e.g., reds and oranges) referred to by a single label (e.g., "orange"). Color and shape labels may be experienced very differently in children's daily life. For instance, color may more often be referred to both as a dimension (e.g., "What color is this?") and as a value (e.g., "See the blue one!") than shape. Little is known about how children map shape labels to shapes during development. One recent study has shed some light on this issue. Verdine, Lucca, Golinkoff, Hirsh-Pasek, and Newcombe (2016) found that toddlers are poor at correctly identifying noncanonical variants of a shape in a forced-choice task context when given a label (e.g., "Find the triangle"), an ability that improves by the preschool years (see also Satlow & Newcombe, 1998).

An understanding of how children perceive, experience, use, and remember feature and dimensional labels can further constrain and help develop the DNF model. Dimensional labels, in particular, play a critical role in Buss and Spencer's (2014) DNF model because the frontal system uses the labels to send a top-down signal to the posterior system to selectively engage processing of a specific dimension. Important questions remain about whether the connection strengths between the frontal and posterior systems might differ across dimensions and how those strengths might change over development. For instance, the strengths of the frontal-to-posterior connection for shape and color might be different depending on children's developmental history with those dimensions and labels. This, in turn, is likely to influence how the label impacts performance in an experimental context (e.g., Yerys & Munakata, 2006).

Limitations and Conclusions

The present report is an important step in establishing a theory–experiment dialog to understand the role of frontal and posterior systems in EF development, but there are some limitations. One limitation is that the children in our control condition—the standard DCCS task—did not participate in a task prior to the DCCS task that engaged them in the same way as the memory game. It is noteworthy that Perone et al. (2015) observed that children who participated in the close shape memory game did not pass the DCCS task, which indicates that actively engaging in an activity prior to the DCCS task is insufficient to help them pass.

Another limitation is that our sample size was relatively small and will need to increase as we begin to use the DNF model to scale toward early EF intervention. For this, we will also need to utilize a randomized control design. However, our sample size has proven reliable across a number of experiments and comparable to the size per condition in other studies using the DCCS task (e.g., Müller, Zelazo, Lurye, & Liebermann, 2008).

There are some important pragmatic implications of our work. For instance, what approach to training EF in children is the best way forward? Many EF training studies have implemented a top-down approach. For example, Espinet et al. (2013) used a form of reflection training in the DCCS task in which 3- to 4-year-old children were asked to pause and think about the rule prior to sorting a card (see also Van Bers et al., 2015). This improved children's performance in the task. Other studies have more explicitly trained EF processes. For example, Blakey and Carroll (2015) trained 4-year-old children's WM by asking them to practice WM tasks (six boxes and one-back tasks), which was associated with improved performance in another WM task (backwards span). Our approach differs from both the top-down and EF process training approaches. We are pursuing a bottom-up-oriented approach that targets the effective neuronal connectivity that underlies rule use. We are doing this by providing relevant experience that increases this effective connectivity. This is guided by a theoretical model that posits that using a rule requires the strong and reliable engagement of neural populations involved in representing the relevant information at hand, such as color or shape. To date, this has proven a promising route because experience in one context (the memory game) helps children flexibly use rules in another (the DCCS task).

The critical pragmatic issue at stake is whether or not this type of training has anything to do with EF in the real world where, ultimately, we would like to strengthen it. For instance, EF is important for school readiness (Mann, Hund, Hesson-McInnis, & Roman, 2017)—does our theory–experiment approach hold any promise for helping children prepare to enter school? It might. Providing children experience that helps them engage the appropriate rule in the appropriate context is critical for successfully adapting to kindergarten. Children must, for instance, remember that they should walk quietly in the hallway and sit still during reading time. These rules are, in fact, often cued by symbols in elementary schools, such as a red sign to walk slowly or sit still. To get from here to there, a number of steps need to be taken. For example, we need to probe whether the type of training used here is lasting, and if it is not, what is required for it to last. We need to probe whether the type of training used here can strengthen other EFs, such as WM or inhibitory control, that frontal–posterior connectivity is also associated with in adults (e.g., Hwang, Velanova, & Luna, 2010; Scherf et al., 2006). We need to probe whether a bottom-up approach can help children use rules in real-world contexts, such as the classroom.

In conclusion, the present report is an important step in establishing a theory–experiment dialog to understand the role of frontal–posterior connectivity in early EF development. In particular, we used the DNF model to probe the utility of targeting effective frontal–posterior connectivity to strengthen EF. Our simulation and empirical results indicate that this is a promising route to promote transfer across task contexts. For instance, we showed that strengthening the effective connectivity associated with the color dimension from the memory game induces dimensional attention in the DCCS task. Inducing dimensional attention might be a powerful intervention tool because behavioral decisions are freed from being so strongly anchored to a specific range of experiences. This may, in turn, enable children to more flexibility adapt to new contexts. The present report indicates that pushing the theory–experiment dialog further can provide a firm base to build upon for early EF interventions.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's website:

Appendix S1. Model Equations and Simulation Method