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# Enhancing the Executive Functions of 3-Year-Olds in the Dimensional Change Card Sort Task

Sammy Perone
*University of Minnesota*

Stephen J. Molitor
*Virginia Commonwealth University*

Aaron T. Buss
*University of Tennessee*

John P. Spencer and Larissa K. Samuelson
*University of Iowa*

Executive functions enable flexible thinking, something young children are notoriously bad at. For instance, in the dimensional change card sort (DCCS) task, 3-year-olds can sort cards by one dimension (shape), but continue to sort by this dimension when asked to switch (to color). This study tests a prediction of a dynamic neural field model that prior experience with the postswitch dimension can enhance 3-year-olds' performance in the DCCS. In Experiment 1A, a matching game was used to preexpose 3-year-olds ($n$ = 36) to color. This facilitated switching from sorting by shape to color. In Experiment 1B, 3-year-olds ($n$ = 18) were preexposed to shape. This did not facilitate switching from sorting by color to shape. The model was used to explain this asymmetry.

Executive functions (EFs) enable humans to think and behave in a flexible, goal-directed fashion. *Executive function* is an umbrella term for a set of interactive control processes that include working memory, inhibition, and attention switching. EFs contribute to children's reasoning (Carlson, Moses, & Breton, 2002), arithmetic (Blair & Razza, 2007), reading (van der Sluis, de Jong, & van der Leij, 2008), and social (Clark, Prior, & Kinsella, 2002) abilities. Moreover, the establishment of robust EFs in early childhood is predictive of positive developmental outcomes, and EF deficits at 3 years of age are predictive of negative outcomes in health, wealth, and criminal activity involvement nearly 30 years later (Moffitt et al., 2011). Not surprisingly, then, EF interventions that positively impact individual development are in great demand.

To date, efforts to develop early interventions to improve EFs have yielded mixed results. Interventions that have trained children's task-switching abilities have transferred to other EFs such as working memory and inhibitory control (Karbach & Kray, 2009). Interventions that have trained children's working memory abilities, by contrast, have not (for reviews, see Diamond, 2012; Shipstead, Hicks, & Engle, 2012). One potential reason that EF intervention efforts have yielded mixed results is that theories of EF development do not predict what contexts training should transfer to because they do not specify the mechanisms by which experience generalizes across contexts (Simmering & Perone, 2013; see also Gibson, Gondoli, Johnson, Steeger, & Morrissey, 2012). For example, theories of EF development do not explain how the same working memory system is used in multiple task contexts. This limitation hinders their ability to specify the types of experience acquired in one context that should influence working memory in another context.

Here, we test a novel prediction of a dynamic neural field (DNF) model of EF development that specifies how experience in one context can facilitate children's performance in a canonical probe of EF in early development—the dimensional change card sort (DCCS) task. In the DCCS, children sort a collection of two-dimensional cards (e.g., red stars and blue circles) to target cards that match on one

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Correspondence concerning this article should be addressed to Sammy Perone, Institute of Child Development, University of Minnesota, 51 East River Road, Minneapolis, MN 55455. Electronic mail may be sent to sperone@umn.edu.

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dimension (e.g., red circle and blue star). After sorting by one dimension, children are instructed to switch the dimension used to sort the same cards. Under these standard conditions, 4-year-old, but not 3-year-old, children flexibly switch attention across dimensions and sort correctly during the postswitch phase (Zelazo, 2006).

The standard DCCS task conditions require children to flexibly switch the dimension to which they attend across the pre- and postswitch phases of the task. A number of studies have shown that 3-year-old children can pass the DCCS task when the standard conditions are simplified or modified such that selective dimensional attention is not required (Brace, Morton, & Munakata, 2006; Brooks, Hanaur, Padowska, & Rosman, 2003). Other studies have shown that 3-year-old children can pass the DCCS task under the standard conditions if they are explicitly pretrained to attend to the bidimensionality of the cards they sort in the DCCS task (Mack, 2007; Ramscar, Dye, Gustafson, & Klein, 2013). No previous study has shown that children can pass the DCCS task under the standard conditions without explicit pretraining. The DNF model predicts that flexible attention switching under the standard conditions of the DCCS task can be induced via prior experience with the label for and features distributed over the feature dimension used in the postswitch phase of the task. In the following section, we describe the DNF model and the basis of this prediction. We then test this prediction with children.

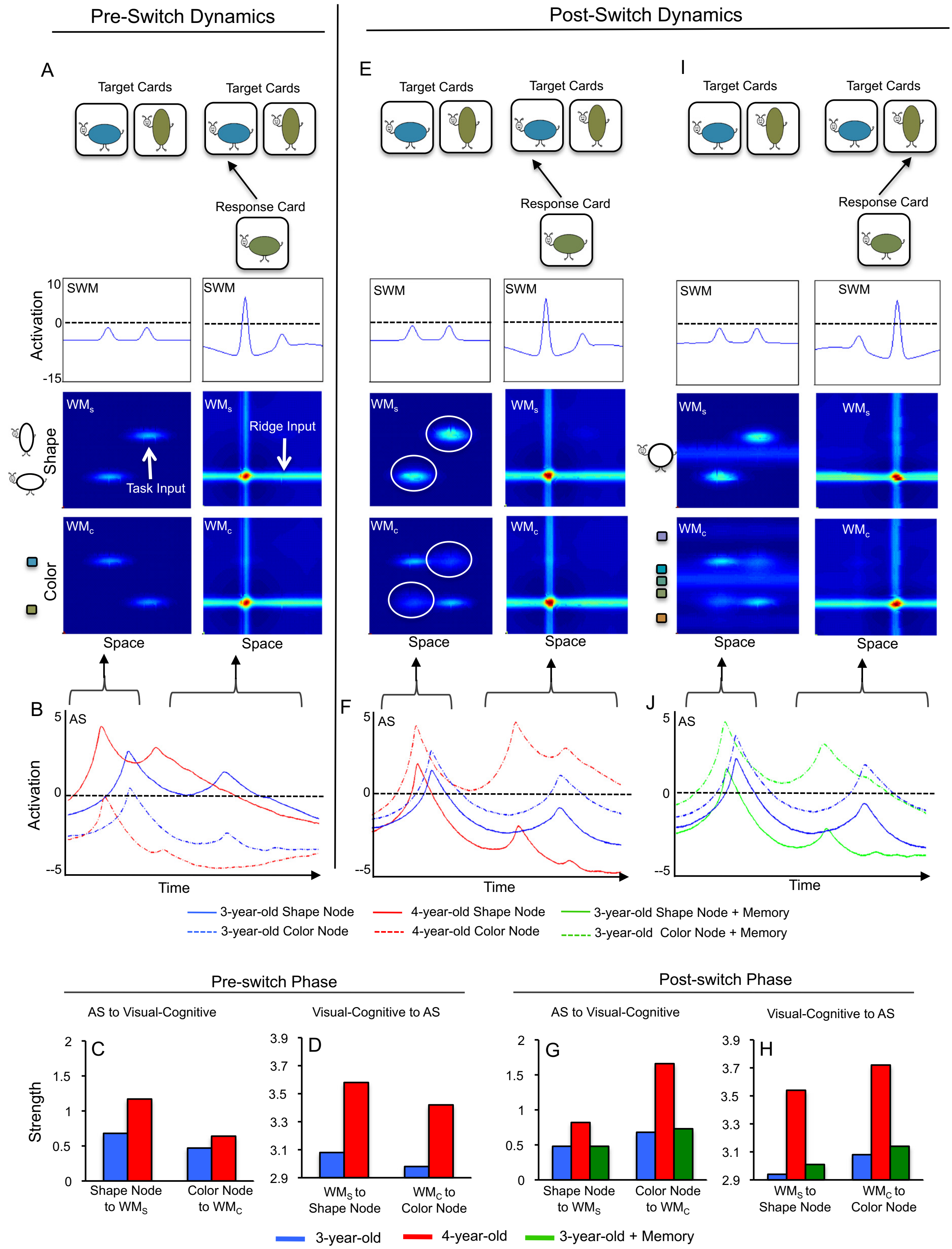
### *A DNF Model of EF Development*

DNF models embody a set of concepts linking brain and behavioral dynamics in real time and over development (for a review, see Spencer, Perone, & Johnson, 2009). The central component of a DNF model is the neural field. Neural fields consist of populations of neurons selectively tuned to continuous dimensions (e.g., hue). The dynamics of neural fields are governed by local excitatory/lateral inhibitory interactions. For example, a blue stimulus excites neurons selectively tuned to the specific hue. These neurons, in turn, excite neurons tuned to similar hues in a graded fashion. This excitation also leads to broad inhibition surrounding the excitation, creating a local excitatory/lateral inhibitory activation profile called a "peak" of activation. One important feature of DNFs is that activity within neural fields creates long-term Hebbian memories that influence their activity at a future point in time. For example, the neuronal response to a blue stimulus will create a long-term memory that strengthens the neuronal response to similar hues at a future point in time.

Buss and Spencer's (2014) model of EF development consists of coupled visual-cognitive and dimensional attention systems (ASs). The left panel of Figure 1A shows the architecture of the model. The visual-cognitive system consists of three interactive working memory fields. Shown at the top of 1A is the spatial working memory (SWM) field. SWM represents the presence of stimuli at specific locations. SWM is coupled to a shape working memory ($WM_S$) field and a color working memory ($WM_C$) field, both of which are shown just below SWM. These fields are sensitive to "what" is "where"; that is, they respond to features distributed along metrically organized feature dimensions such as hue
(*y*-axis) at spatially specific locations (*x*-axis). The connection of $WM_S$ and $WM_C$ to SWM enables the model to represent objects as a color and a shape at a particular location (e.g., red + star on the left). The AS consists of competitive nodes that respond to the labels "shape" and "color" that control attention switching across dimensions (1B). These nodes are coupled to $WM_S$ and $WM_C$ via a weight matrix that represents learned associations between the labels (e.g., "color") and the feature values (e.g., blue) the labels represent.

Buss and Spencer (2014) created 3- and 4-year-old models by making two changes to the AS. First, older models had stronger excitatory and inhibitory interaction strengths within the AS making the shape and color nodes more competitive (winner-take-all interactions) and better able to maintain excitatory interaction once one node "won" the competition. Second, the older model had a more selective weight matrix between the AS and the visual-cognitive system—the color node, for instance, projected greater activation to $WM_C$ and less activation to $WM_S$. Buss and Spencer used the 3- and 4-year-old models to quantitatively simulate developmental changes in children's performance in the DCCS task across 14 variants of the task and to generate and test novel behavioral predictions. Our goal here was to probe ways to facilitate the performance of the same 3-year-old model used by Buss and Spencer. Note that all model details including equations and parameter settings can be found in Buss and Spencer.

Figure 1 illustrates how the 3- and 4-year-old models perform the DCCS task. Figure 1A shows the DNF model during the preswitch phase of the task. The very top shows target cards present at left (short, blue object) and right (tall, green object) locations. These target cards provide task input to SWM and generate "bumps" of activation at left and right locations in SWM.



The target cards also provide task input to $WM_S$ and $WM_C$. As indicated by the light blue patches of activity in these fields, the target card depicting the tall, green object generates an increase in activation at the tall value in $WM_S$ (see "task input" in Figure 1A) and at the green value in $WM_C$. Similarly, the target card depicting the short, blue object generates an increase in activation on the left side of $WM_S$ and $WM_C$.

At the onset of the preswitch phase, the DNF model is instructed to sort by shape. This selectively activates the shape node in the AS. The activation of the shape node is shown in 1B for the 3-year-old model (solid blue line) and 4-year-old model (solid red line). Because the shape node is activated, this node sends stronger activation to $WM_S$ than the color node sends to $WM_C$. This difference in input strength from the AS to the visual-cognitive system is quantified in 1C: The activation from the shape node to $WM_S$ is stronger than the activation of the color node to $WM_C$ for both the 3-year-old model (blue bars) and 4-year-old model (red bars). This raises the baseline activity of neurons within $WM_S$, effectively priming the system to selectively attend to the shape dimension. Note that the strength difference in 1C is greater for the 4-year-old model because the nodes have stronger excitatory/inhibitory interactions and because the weight matrix connecting the AS to the visual-cognitive system is more selective.

Figure 1D shows that the priming effect also has an impact on the AS. In particular, because the AS and the visual-cognitive system are reciprocally connected, the priming leads to an increase in the strength of activation $WM_S$ sends back to the shape node. This feedback from the visual-cognitive system to the AS is stronger for shape than color for both the 3- and 4-year-old models, although the activation strengths are greater for the 4-year-old model due to the more selective weight matrix.

Next, the model is presented with a response card depicting a short, green object (right panels in 1A). This provides a ridge of input across all spatial locations activating all neurons tuned to the short feature in $WM_S$ and the green hue in $WM_C$ (see "ridge input" in 1A). Recall that because of the task instructions, $WM_S$ is primed to respond more strongly to shape stimuli than $WM_C$ is to color stimuli. Consequently, the overlap of the ridge input from the response card with the task input from the target input in $WM_S$ creates an activation peak at the left location associated with the short stimulus (see red "hot spot" of activation in $WM_S$). This peak is a real-time neuronal representation of the shape of the short object at the left location. The peak excites neurons tuned to the left location in $WM_C$ and SWM, leading to peaks in both fields, effectively "binding" the short feature in $WM_S$ to the green feature in $WM_C$. Consequently, the model

*Figure 1.* The dynamic neural field (DNF) model dynamics for 3- and 4-year-old models in dimensional change card sort task are illustrated. Panel A shows the model dynamics during the preswitch phase. Initially, the model is situated in front of target cards depicting a short, blue object and a tall, green object. This generates task inputs in spatial working memory (SWM; see "bumps") and shape working memory ($WM_S$) and color working memory ($WM_C$; see light blue patches). The model is instructed to sort the short, green object depicted on the response card by shape. This leads the shape node in the attention system (AS) to become active for the 3- and 4-year-old models (see solid blue and solid red lines in B). Consequently, the strength of the connectivity between the AS and the visual-cognitive system is stronger for shape than color node (compare left portion to right portion of C-D). It is also stronger for the 4-year-old than 3-year-old model (compare red bars to blue bars in C-D). This reflects the stronger connectivity in the 4-year-old than 3-year-old model (see text). These interactions between the AS and visual-cognitive system lead the model to sort by shape by forming activation peaks in $WM_S$, $WM_C$, and SWM at the left location. Note that the arrows shown from the AS to the visual-cognitive system indicate the window of time that AS activity corresponds to the onset of a trial (left portion of A) and the sorting of the card (right portion of A). Panel E shows the DNF model dynamics during the postswitch phase. The model is instructed to sort the short, green object by color. This leads the color node in the AS to become active for the 3- and 4-year-old models (see dashed blue and dashed red lines in F). During the postswitch phase, the strength of the connectivity between the AS and visual-cognitive system is stronger for color than for shape (compare right portions of G-H). It is also stronger for the 4-year-old than the 3-year-old model (compare red to blue bars in G-H). Importantly, for the 3-year-old model, this connectivity is too weak for $WM_C$ to overcome the robust Hebbian memories acquired from sorting by shape during the preswitch phase in $WM_S$ (see white circles). The 3-year-old model continues to sort the short, green object to the left location by shape. The 4-year-old model sorts by color (not shown). Panel I shows the 3-year-old model during the postswitch phase after it has acquired experience in the form of Hebbian memories with the dimensional label "color" in the AS and 5 objects that differ in color (see distributed light blue patches in $WM_C$) and share one shape (see light blue ridge in $WM_S$). This experience primes $WM_C$ to respond more strongly during the postswitch phase. It also creates a stronger pattern of connectivity from the AS to the visual-cognitive system for color than shape (green bars in G) and from the visual-cognitive system to the AS for color (green bars in H) than in the 3-year-old model alone for color (blue bars in G-H). This is also reflected in the strength of the color node in the AS, which is stronger for the 3-year-old + memory model than 3-year-old model alone (compare dashed green line to dashed blue line in the AS in J). The 3-year-old model switches attention across dimensions and sorts the short, green object to the right location based on color in the postswitch phase.

sorts the response card to the left location, correctly attending to the shape on the card.

There are two influences on attention switching during the postswitch phase. The first is a Hebbian memory. The presence of peaks in the working memory fields creates Hebbian memories that accumulate slowly over trials. These Hebbian memories facilitate the re-formation of peaks at previously active sites in the working memory fields. Sorting the response cards in the preswitch phase leads to the accumulation of Hebbian memories in $WM_S$ and $WM_C$ at sites associated with the sorting responses (e.g., at short and green feature values). This can be seen in the left panel of 1E, which shows the state of the model at the onset of the postswitch phase. In $WM_S$, there is cooperation between the Hebbian memories and task inputs (white circles) because the model sorted response cards based on a match in shape (i.e., short objects to the left and tall objects to the right). Consequently, the model is primed to continue sorting by shape. In $WM_C$, by contrast, there is competition: Hebbian memories (white circles) accumulated at sites that did not overlap with the task inputs because the model sorted response cards to target cards that did not match in color.

The second influence on attention switching during the postswitch phase is the state of the AS. At the onset of the postswitch phase, the model is instructed to sort by color instead of shape. As is shown in 1F, this selectively activates the color node for the 3-year-old model (dashed blue line) and 4-year-old model (dashed red line). Consequently, the activation sent from the color node to $WM_C$ (see 1G) is stronger than the activation sent from the shape node to $WM_S$ for both the 3-year-old model (blue bars) and 4-year-old model (red bars). The activation returned from $WM_C$ to the color node is also stronger than the activation returned from $WM_S$ to the shape node (1H). Importantly, the degree to which $WM_C$ is primed to respond to color is less for the 3-year-old model than the 4-year-old model due to weaker excitation/inhibition within the AS and a less selective weight matrix between the AS and the visual-cognitive system.

This weaker priming has consequences in the postswitch phase because the system must overcome the response biases created during the preswitch phase. In particular, when the 3-year-old model is presented with the short, green response card in the right panels of 1E, it sorts the card based on shape. The color priming was not sufficient to overcome the cooperation between Hebbian memories and task input in $WM_S$. By contrast, the 4-year-old model sorts correctly during the postswitch phase (not shown; see Buss & Spencer, 2014, for example simulations) because the color priming effect is much stronger (see Figure 1G and H).

In summary, the 3-year-old model fails the DCCS task because there is strong cooperativity within the preswitch working memory field (in this case, $WM_S$) and the AS activity is weak and not yet selective. But what if we could somehow boost attention to the postswitch dimension, in this example, color? One way to do this is to give the model experience with different hue values in the context of the label "color." These experiences should leave distributed Hebbian memories within $WM_C$ and stronger "color" memories in the AS, effectively "boosting" the degree to which the model is primed to respond to color during the postswitch phase of the task. Such a boost might be sufficient to tip the scales toward the color dimension during the postswitch phase.

Figure 1I implements this idea in the 3-year-old model (see the Appendix S1 in the online Supporting Information for additional simulation details). In these simulations, the color node was initialized with a slightly stronger Hebbian memory reflecting recent experiences with the label "color," priming the color node to respond more strongly to "color" than it would without this experience. The model was also initialized with Hebbian memories for a collection of objects experienced outside the context of the DCCS task that all shared the same shape but varied in color. Importantly, we did not use any of the feature values used in the DCCS task. The resultant Hebbian memories are shown in the left panels of 1I. There is a localized memory on the shape dimension (light blue ridge at center of shape dimension in $WM_S$). This reflects the one shape shared by all colors experienced prior to the DCCS task. There are distributed memories on the color dimension (light blue patches along entire color dimension in $WM_C$). This reflects the variable colors the model was exposed to prior to the DCCS task. These memories elevate the neural activity across the color dimension in $WM_C$, priming $WM_C$ to respond more robustly to color stimuli than it would without this prior experience.

This priming had a big impact on the performance of the 3-year-old model in the DCCS task. This is evident in the right panels of 1I, which show performance during the postswitch phase. When the model is presented with the short, green response card at the onset of the postswitch phase and is instructed to sort by color, the label input and Hebbian memories in the AS and $WM_C$

combine to create a stronger boost for color. The model sorts the short, green card to the right by color.

The influence of the Hebbian memories on the model's dynamics is evident in the reciprocal interaction between the AS and visual-cognitive system. In particular, the slight increase in the Hebbian memories at the start of the simulation creates stronger activation from the color node to $WM_C$ (1G) and stronger activation from $WM_C$ to the color node (1H) during the postswitch phase for the 3-year-old model with Hebbian memories (green bars) relative to the standard 3-year-old model (blue bars). This can also be seen in 1J, which shows the stronger activation of the color node for the model with prior experience (dashed green line) relative to the standard 3-year-old model (dashed blue line). This slight initial boost for color is sufficient to tip the balance during the postswitch phase of the task and the 3-year-old model correctly switches attention from shape to color.

### *Quantitative Model Predictions*

We quantitatively probed this prediction using the 3-year-old model, parameters, and simulation method from Buss and Spencer (2014). The distribution of the stimulus inputs is shown in Figure 2. The inputs were sampled from a set of 18 equidistant metric steps on the shape and color dimensions, which were distributed over 100 neurons in the model. Each metric step in the model for color and for shape was separated by four neurons. Each object consisted of one feature from the shape dimension and one feature from the color dimension. For example, stimulus s5c5 is the fifth feature on the shape and color dimensions. The values s5c5 and s14c14 (squares) were used as target cards. The values s14c5 and s5c14 (circles) were used as response cards. The model was instructed to sort each response card 3 times by shape during the preswitch phase and each response card 3 times by color during the postswitch phase. When sorting by shape during the preswitch phase, sorting response card s14c5 to target card s14c14 and response card s5c14 to s5c5 was the correct response because they share the same shape. When sorting by color during the postswitch phase, sorting response card s14c5 to target card s5c5 and response card s5c14 to s14c14 was the correct response because they share the same color. The model was run through the DCCS task 100 times under these standard conditions. To pass the DCCS task, it was required to correctly sort five of the six cards during the postswitch phase. The model passed at a rate of 30% (Figure 3). The model was also run through a memory + standard condition 100 times. It was initialized with Hebbian memories for five colors that spanned the color dimension (1, 6, 10, 13, and 18), all paired with the same shape (10). The strength of the memories for the five colors was set to .2 (the strength of the memory for the single shape shared by all colors was set to .6). The model passed at a rate of 81% (Figure 3).

Previous studies have shown that children can pass the DCCS task when the standard conditions are simplified (Brace et al., 2006) or children are explicitly pretrained to attend to the features on both dimensions on the response cards used in the DCCS task (Mack, 2007; Ramscar et al., 2013). The DNF model predicts that attention switching in 3-year-old children can be induced by experience with the postswitch dimension even when the features used in the DCCS task are not part of that experience and the preexposure happens in a different task context. We tested this prediction in Experiment 1A.

## Experiment 1A

### *Method*

#### *Participants*

Eighteen 3-year-old (9 girls, $M$ = 42.50 months, $SD$ = 2.84) children participated in a memory game + standard DCCS condition. One additional child participated but was excluded for failing to sort 5 of 6 cards correctly during the preswitch phase (see Zelazo, 2006). Eighteen 3-year-old children (10 girls, $M$ = 41.30 months, $SD$ = 2.30) participated in the standard DCCS task only. Four additional children participated but were excluded due to fussiness ($n$ = 2) and failing to sort five of six cards correctly during the preswitch phase ($n$ = 2). Children were recruited from birth records and local child-care facilities.

#### *Stimuli, Design, and Procedure*

The stimulus set from which the target, sorting, and memory game (described below) cards were derived were buggles (see Figure 2; Perone & Spencer, 2014). The set is a collection of objects that consist of one value along continuous color (hue) and shape (aspect ratio) dimensions. On the color dimension, 18 equidistant colors were sampled from 1° to 180° of a 360° continuous color space (CIE*Lab, 1976). The shape dimension was parsed

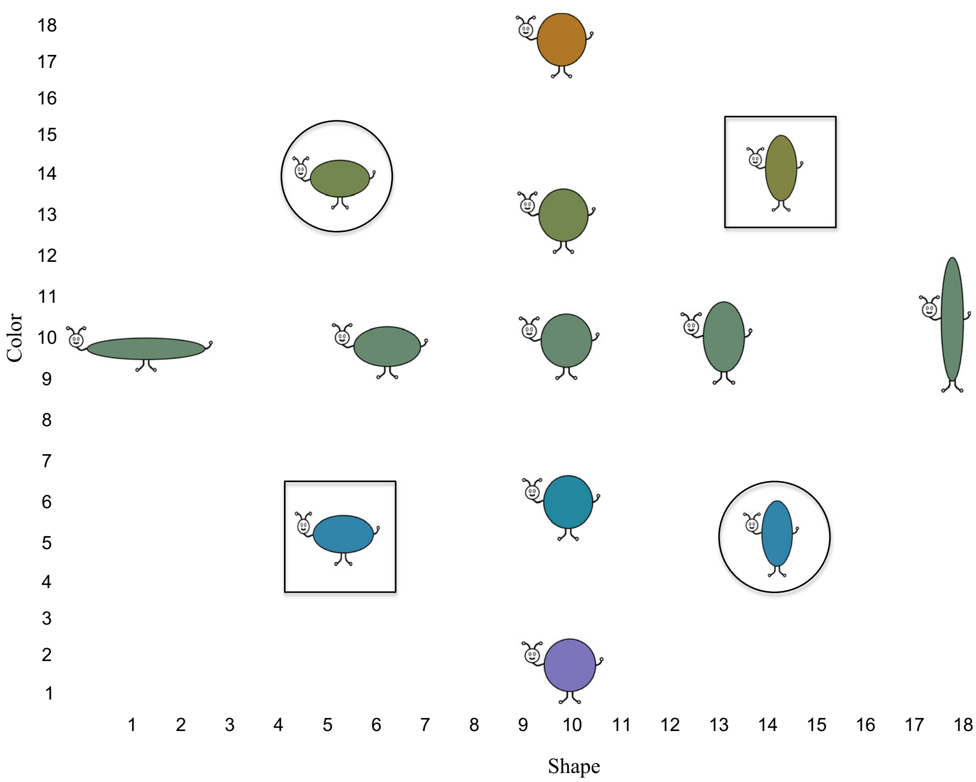



*Figure 2.* The buggle stimulus set is shown. Each buggle consists of one value along a continuous, metrically organized color (hue) and shape (aspect ratio) dimension. The entire shape dimension consisted of 18 equidistant metric steps. The entire color dimension consisted of 1–180° of a 360° color space (CIE*Lab, 1976), equally parsed to create 18 equidistant metric steps. The objects with squares were used as target (or response) cards, and the objects with circles were used as response (or target) cards. The objects sharing shape 10 but varying in color were used in the color memory game to expose children to what would be the postswitch dimension in Experiment 1A. The objects sharing color 10 but varying in shape were used in the shape memory game to expose children to what would be the postswitch dimension in Experiment 1B. The same shape and color values were used as input to the dynamic neural field model.

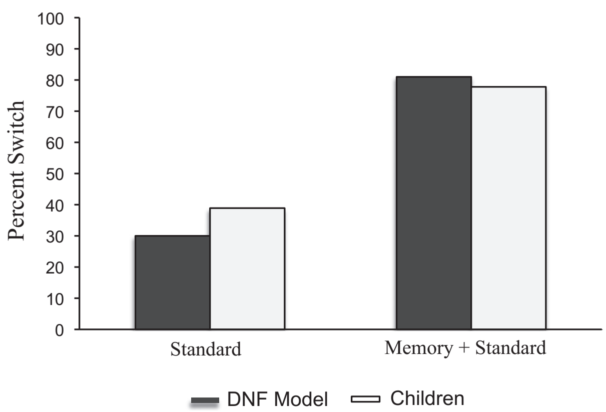



*Figure 3.* The plots show the percentage of dynamic neural field model simulations (black bars) and children (white bars) who passed the postswitch phase of the dimensional change card sort task under the standard conditions and in the memory + standard condition in Experiment 1A.

into 18 equidistant steps. Each metric step was defined by a proportional change in height and width, with total area held constant.

The color and shape values used were the same as those used in the DNF model. For the DCCS task, there were two sets of cards. For one set, s5c5/s14c14 were target cards and s14c5/s5c14 were response cards. For the other set, s5c14/s14c5 were target cards and s5c5/s14c14 were sorting cards. The set of cards used was counterbalanced across children. The goal of the standard condition was to ensure that 3-year-old children pass the DCCS at rates comparable to that observed in the literature with this new, metrically organized stimulus set. Given this goal, it was important for half of the children to sort by shape during the preswitch phase and the other half of the children sort by color.

The standard conditions followed Zelazo's (2006) protocol. The experimenter told the child the preswitch rule ("We are going to play the shape game"). The experimenter showed the child how to sort one card by the preswitch dimension and ensured that the child could do so with another card. During the preswitch phase, the experimenter presented each response card, labeled it along the preswitch dimension ("Here's a blue buggle"), and asked the child to sort the card ("Can you put it where it goes?"). If the child sorted incorrectly, the preswitch rules were restated. At the onset of the postswitch phase, the experimenter explained the postswitch rule ("Now we are going to play the color game") but did not show the child how to sort the cards by the postswitch rule. The postswitch phase was otherwise identical to the preswitch phase. Children sorted each response card three times each. The order of the cards was random with the constraint that no more than two identical cards were presented on consecutive trials.

Children in the memory + standard condition played a memory game much like those sold commercially or played with a standard deck of cards. The goal of the memory game was to expose children to what would be the postswitch dimension in the DCCS task in an engaging task appropriate for the age group. For all children in the memory + standard condition, the preswitch dimension was shape and the postswitch dimension was color. During the memory game, children matched five pairs of cards depicting the same shape and color values used in the DNF model. The same shape (10) was used for all cards but the colors spanned the color dimension (1, 6, 10, 13, 18; see Figure 2).

The experimenter and child sat at a table with the matching cards spread out face up within reaching distance. The experimenter familiarized the child with each matching pair of cards by showing the child each card and its match together. The experimenter said to the child, "Look! These two are the same color" to help ensure the child was engaged in the familiarization phase. The experimenter only labeled the dimension (i.e., color) and did not label any of the individual color values (e.g., blue). After the child was familiar with each pair, the experimenter flipped all the cards over so that they were face down and scrambled them. The experimenter then explained to the child that they were going to try to find the colors that matched. The experimenter provided a demonstration by turning over two nonmatching cards, one at a time, and said, "These two aren't the same color." The experimenter then flipped the two nonmatching cards back over and told the child it was his or her turn. The child and experimenter took turns flipping over pairs of cards. If the pair was a match, then the cards were removed from the game. If the pair was not a match, both cards were flipped back over. Each child was required to find four of the five matches during the game. The experimenter randomly selected nonmatching pairs of cards during his or her turn, until only four cards remained in the game. The experimenter then selected a matching pair to allow the child to uncover the final matching pair. It is notable that children may solve the memory game via trial and error or randomly flipping over cards rather than finding matches by relying on memory of the colors of previously flipped over cards. However, previous studies have shown that children of this age form working memories even for rapidly presented stimuli (Simmering, 2012); thus, even if children's performance was based on trial and error, they likely formed memories for the color values. Once all the matches were found, the DCCS task was administered.

### *Results*

Children were considered to pass the postswitch phase of the DCCS task if they correctly sorted five of the six cards presented during the postswitch phase (Zelazo, 2006). Only 7 of 18 (38.9%) children passed the standard condition of the DCCS task with our metrically organized stimulus set (Figure 3), replicating previous findings (Zelazo, Müller, Frye, & Markovitch, 2003). Of the 7 children who passed, 3 sorted by color during the preswitch phase and 4 sorted by shape during the preswitch phase. The rate of passing did not differ by preswitch dimension, $\chi^2(1, N = 18) = 0.234$, $p = .629$. Results for the memory + standard condition were strikingly different: Fourteen of 18 children (77.8%) passed the DCCS task (Figure 3). A chi-square analysis revealed that significantly more 3-year-old children passed in the memory game + standard condition than in the standard condition alone, $\chi^2(1, N = 36) = 5.60$, $p = .018$. Thus, 3-year-old children flexibly switched attention from the shape to the color dimension under the standard conditions of the DCCS task after acquiring prior experience with the postswitch dimension.

### *Discussion*

The results of Experiment 1A are consistent with the DNF model prediction that experience with colors prior to the DCCS task can induce flexible attention switching from shape to color in 3-year-old children. Previous studies have shown that children can pass the DCCS task when the standard conditions are simplified (Brace et al., 2006) or children are explicitly pretrained to attend to the features on both dimensions on the response cards used in the DCCS task (Mack, 2007; Ramscar et al., 2013). Here, however, children's flexibility was induced under the standard conditions without explicit task-specific pretraining or simplification.

One open question is whether flexible attention switching in the DCCS can also be induced for the shape dimension. Our simulations of the DNF model treated the color and shape dimensions equivalently. That is, the metric organization of the colors and shapes was identical for both dimensions in the model. Nevertheless, previous studies have observed asymmetries in children's DCCS performance based on the dimension they sort by during the postswitch phase. For example, Fisher (2011) found that 3-year-old children failed a version of the DCCS task when they were asked to switch from a dimension with distinct features (e.g., star and flower) to a dimension with similar features (e.g., pink and red), but not when they were asked to switch from similar features to distinct features. Although children failed our DCCS task under the standard conditions regardless of whether they were sorting by color or by shape during the postswitch phase, it is possible that a memory game for the shapes used here would not influence children in the same way as color did. Thus, in Experiment 1B we tested whether experience with values distributed over the shape dimension could induce flexible attention switching from color to shape.

## Experiment 1B

### *Method*

#### *Participants*

Eighteen 3-year-old children (8 girls, $M$ = 41.36 months, $SD$ = 4.84) participated in this study. Nine additional children participated but were excluded due to fussiness ($n$ = 2), experimenter error ($n$ = 6), or failing the preswitch phase ($n$ = 1). Children were recruited from birth records, university community, and child-care facilities.

#### *Stimuli, Design, and Procedure*

The stimuli, design, and procedure were identical to Experiment 1A with two exceptions. First, children matched by shape instead of color during the memory game with the same metric distribution of values over the shape dimension as was used for the color dimension in Experiment 1A (see Figure 2). Second, children sorted by color during the preswitch phase of the DCCS task and shape during the postswitch phase.

### *Results*

One child was excluded from the final analysis because he or she failed the preswitch phase of the task. Eight of 18 (44.4%) children passed the postswitch phase of the task (Figure 4). A chi-square analysis revealed that the number of 3-year-old children who passed the shape memory game + standard condition was not significantly different from the number of children who passed under the standard conditions alone, $\chi^2(1, N = 36) = 0.11$, $p = .74$, but was significantly less than the number of children who passed in the color memory game + standard condition, $\chi^2(1, N = 36) = 4.21$, $p = .04$. Thus, the experience provided during the shape memory game prior to participating in the DCCS task did not facilitate 3-year-old children's ability to flexibly switch attention from color to shape.

### *Discussion*

The results indicate that experience with the color and shape dimensions used here do not influence children's ability to flexibly switch attention across dimensions in the DCCS task in the same way. Why might this be? For insight, we return to results from Fisher (2011) showing that 3-year-old children failed a version of the DCCS task when they were asked to switch from a dimension with distinct features to a dimension with similar features, but not when they were asked to switch from similar features to distinct features. Buss and Spencer (2014) quantitatively simulated results from this study by changing the metric distribution of features used in the DNF model. When model inputs were compressed along one dimension making the inputs less distinctive along that dimension, the model failed the DCCS task if this less distinctive dimension was used as the postswitch dimension. By contrast, when the less distinctive dimension was the preswitch dimension, the model correctly switched rules in the postswitch phase.

Based on these findings, we hypothesized that the asymmetry in the present study might reflect a similar asymmetry in the distinctiveness of the color and shape dimensions. In particular, we hypothesized that the shape dimension was less distinctive; that is, adjacent steps along the shape dimension were compressed relative to steps along

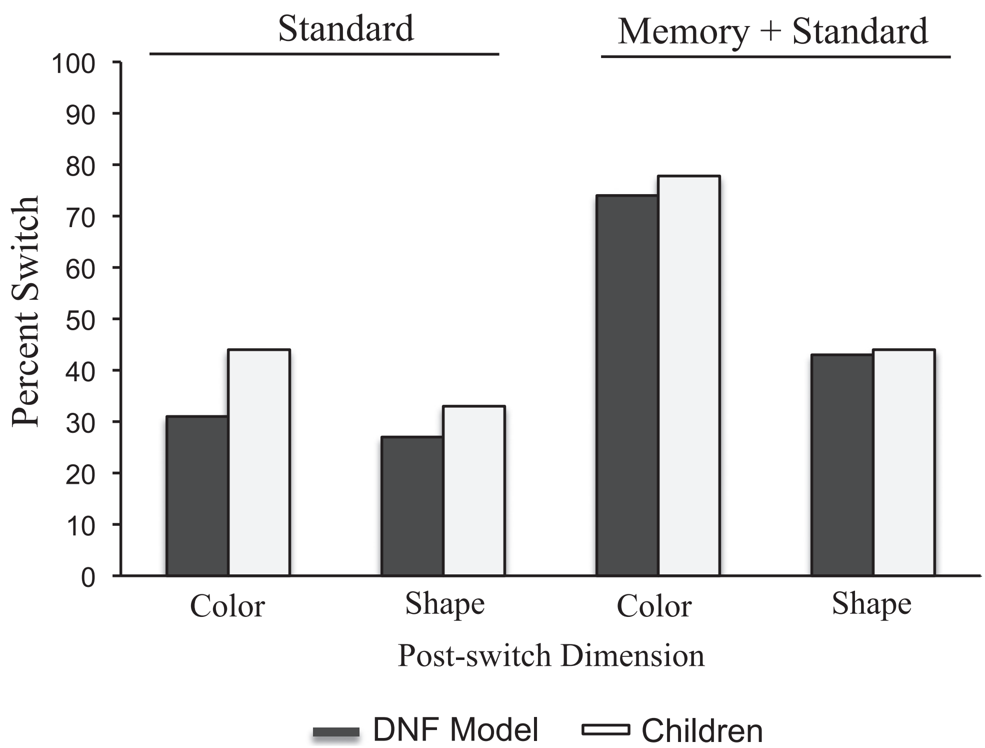



*Figure 4.* The results across Experiments 1A and 1B are shown. The left portion shows the percentage of dynamic neural field (DNF) model simulations (black bars) and children (white bars) who passed the postswitch phase of the dimensional change card sort task under the standard conditions when the postswitch dimension was color and when the postswitch dimension was shape (Experiment 1A). The right portion shows the percentage of DNF model simulations (black bars) and children (white bars) who passed the post-switch phase after the color memory game (Experiment 1A) and the shape memory game (Experiment 1B).

the color dimension. The critical question here is how this asymmetry might impact the memories carried forward from the shape memory game to the DCCS task.

To explore this, we constructed a simplified, one-dimensional DNF model that enabled us to probe how experience with a distributed versus compressed set of stimuli would influence working memory peaks and Hebbian memories across a series of learning trials comparable to what children might experience in the memory game (for model details, see Appendix S1). Figure 5 shows these simulations. The top of 5A shows the metric organization of colors used in Experiment 1A. Each metric step on the 18-step dimension is separated by 4 neurons in a neural population of 100 neurons selectively tuned to color. With this separation of values in color space, there is a substantial neural territory devoted to each color. The middle panel of 5A shows a working memory field for color ($WM_{C\_1D}$), and the bottom panel shows an associated Hebbian layer for color ($HL_{C\_1D}$). This model was presented with the five color values used in the color memory game in a random order across 30 learning trials, much like successively flipping over cards in the color memory game while seeking matches. Figure 5A shows the model early in learning. The model is maintaining a working memory for color 13 and has accumulated Hebbian memories for colors 1 and 10 on previous trials. Figure 5B shows the model a bit later in learning. Now, the model is maintaining a working memory for color 1, but critically, it is also maintaining a working memory for color 10 that was presented in the just-recent past. This enables the model to form robust Hebbian memories for both items. This learning process continues across trials, leading to strong Hebbian memories for all colors from the memory game (5C).

Figure 5D–F shows what emerges when the model is presented with shapes that are less distinctive, that is, with shapes that are compressed together along the metric feature dimension (see top panel of 5D). In particular, each metric step on the 18-step dimension is separated by just 1.5 neurons in a neural population of 100 neurons selectively tuned to shape. With this small step size in shape space, there is little neural territory devoted

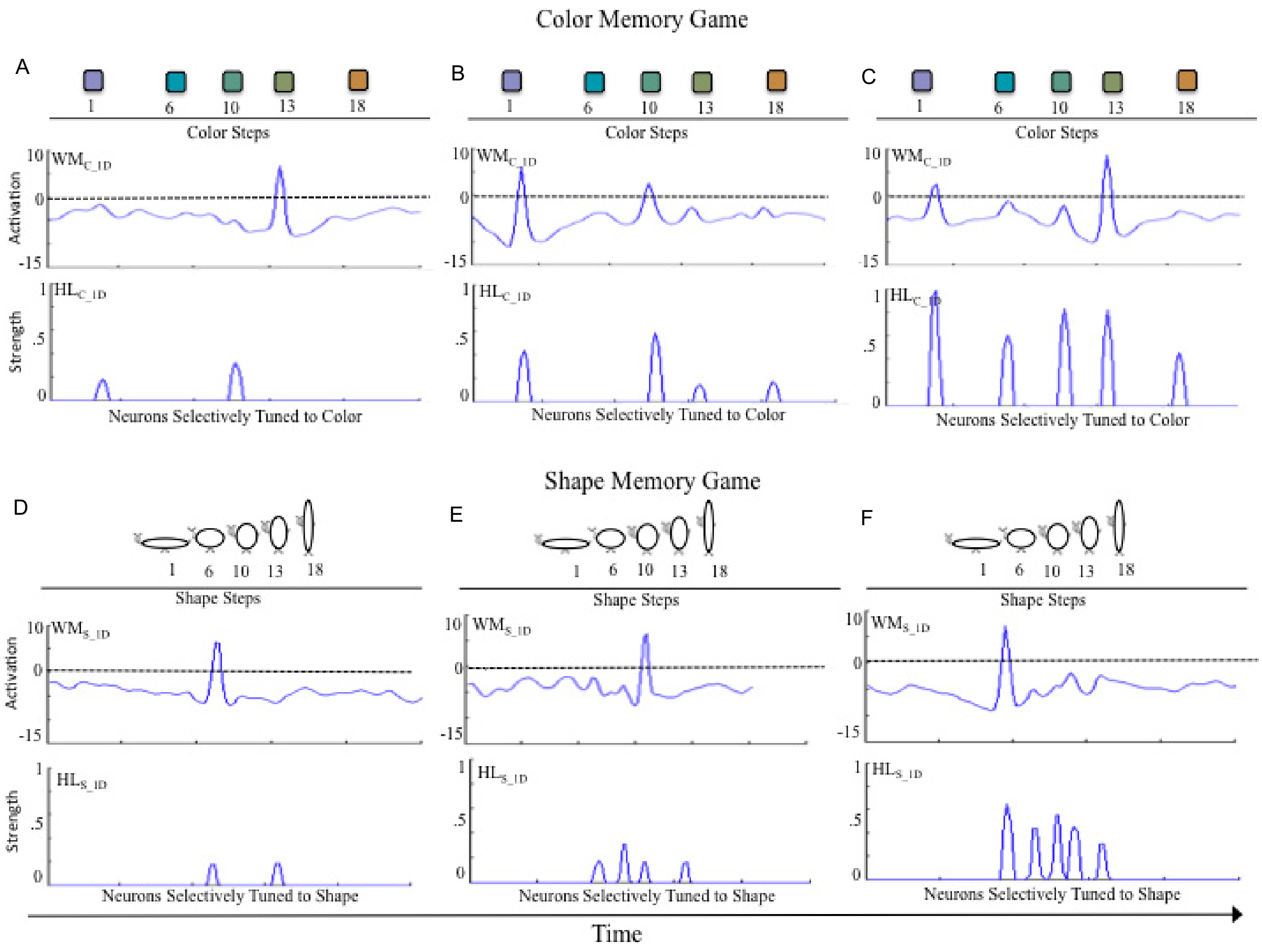



*Figure 5.* Simulations of a one-dimensional dynamic neural field model of the color memory game (top portion) and shape memory game (bottom portion) are shown. The top of Panel A shows the metric organization of the color values used in the color memory game. This is the input to a one-dimensional working memory field for color ($WM_{C\_1D}$), shown just below. $WM_{C\_1D}$ is coupled to a Hebbian layer for colors ($HL_{C\_1D}$). Panel A also shows the model early in learning, after exposure to just a couple of colors in the color memory game. At this time, the model has acquired a couple of weak memories in $HL_{C\_1D}$. Panel C shows the model a bit later in learning. Now, the model has acquired more memories in $HL_{C\_1D}$, some of which are robust. It is also maintaining multiple items in $WM_{C\_1D}$, which helps the model acquire even more robust memories in $HL_{C\_1D}$. By the end of learning, late in the color memory game, the model has acquired robust memories in $HL_{C\_1D}$ for all the colors in the color memory game. The top of Panel D shows the metric organization of the shape values used in the shape memory game. These are noticeably closer than those used in the color memory game, even though the distribution is the same. These values were input into a one-dimensional working memory field for shape ($WM_{S\_1D}$). Panel D also shows the model early in learning, after exposure to just a couple of shapes in the shape memory game. The model has a couple of weak memories in the associated Hebbian layer, $HL_{S\_1D}$. Panel E shows the model a bit later in learning. The model has acquired memories for several shapes in $HL_{S\_1D}$. Notice that $WM_{S\_1D}$ is only maintaining one item, as compared to two in $WM_{C\_1D}$ at the same time in learning in the color memory game (see B). This is because the closeness of the shape values creates interference in $WM_{S\_1D}$, effectively limiting it to remembering only one item at a time. This, in turn, hinders the ability of the model to form robust memories in $HL_{S\_1D}$ during the course of the shape memory game (F).

to each shape. This has a dramatic impact on learning about shapes in the model. Figure 5D shows the model early in learning. At this point, the model is maintaining a working memory of shape 6 and has accumulated Hebbian memories for shapes 1 and 6. A bit later in learning, the model is still only maintaining one shape in working memory (5E). This contrasts with the same model learning about colors in 5B—that model was able to maintain multiple colors in working memory at the same point in learning. What is the source of this difference? The close proximity of shape values leads to working memory peaks that inhibit each other. When a new working memory peak is formed, the lateral inhibition surrounding it effectively knocks out any existing working memory peaks that are close by (see inhibitory troughs surrounding peaks in 5D–F). This interferes with the formation of

Hebbian memories, ultimately leading to weak Hebbian memories for the individual shapes over learning (5F). These weaker Hebbian memories for shapes, relative to those for colors (5C), may be insufficient to prime the shape dimension in the DCCS task. These simulations are consistent with recent evidence showing that young children's performance in a working memory task was poorer for similar items than dissimilar items (Simmering & Cooper, 2014).

To probe whether this account might explain the asymmetry we observed across Experiments 1A and 1B, we conducted a second set of quantitative simulations. In particular, we resimulated the model, testing the hypothesis that weaker Hebbian memory strengths for less distinctive shapes relative to stronger Hebbian memory strengths for colors could account for the pattern of behavioral results observed in Experiments 1A and 1B.

### *Quantitative Model Simulations of Dimensional Asymmetry*

To resimulate the DNF model and test whether the asymmetry across Experiments 1A and 1B might reflect differences in the distinctiveness of the colors versus shapes used in our stimulus set, we used the metric organization of the color and shape dimensions shown in Figure 5. The 18 metric steps on the color dimension were distributed as in Experiment 1A with each step separated by four neurons as illustrated in 5A. The 18 metric steps on the shape dimension, by contrast, were each separated by 1.5 neurons as illustrated in 5D. Recall that the metric organization of the stimulus inputs was identical on the shape and color dimensions in our previous simulations. Moreover, Buss and Spencer (2014) showed that the metric distribution of inputs can have an impact on performance in the standard DCCS task. Thus, the first set of simulations below tested whether the DNF model produces the same pattern of results in the standard task (see Figure 3) with the distribution of inputs compressed along the shape dimension (see Figure 5).

Next, we simulated the color memory game + standard condition using inputs compressed along the shape dimension. The goal of these simulations was to examine whether the novel prediction from Experiment 1A was replicated with the new input distribution for shape when color was the postswitch dimension in the DCCS task. The strength of the memories for the five colors was set to .2 (the strength of the memory for the single shape shared by all colors was set to .0375). Finally, we simulated the shape memory game + standard condition. Here, we once again used inputs compressed along the shape dimension. The strength of the initial Hebbian memories for the shapes used in the shape memory game was reduced relative to the colors used in the color memory game to reflect the weaker learning revealed in our previous simulations (see Figure 5). The strength of the memories for the five shapes was set to .025 (the strength of the memory for the single color shared by all shapes was set to .3). All simulation sets consisted of 100 simulations of the 3-year-old model from Buss and Spencer (2014).

Simulation results are shown in Figure 4 along with children's performance from Experiments 1A and 1B. The DNF model performed similarly to children across all conditions. Specifically, the model with compressed inputs along the shape dimension showed low rates of passing under the standard conditions regardless of whether color or shape was the postswitch dimension. For the color memory game + standard, the DNF model correctly switched and sorted by color in the postswitch phase as before, replicating the novel prediction from Experiment 1A. By contrast, for the shape memory game + standard, the DNF model failed to switch to shape in the postswitch phase. Thus, the close metric separation for shapes did not influence the model's performance under the standard conditions or the color memory + standard condition. For the shape memory game + standard condition, by contrast, the model, like children, failed to switch attention to shape. These simulations provide support for the hypothesis that the asymmetry in our empirical results might arise from a shape dimension that is less distinctive.

## General Discussion

The present study showed that experience with a metrically organized feature dimension in a memory-matching game can enhance attention switching in the DCCS task. This is the first demonstration that young children can pass the DCCS task under the standard conditions without simplification (Brace et al., 2006; Brooks et al., 2003) or explicit pretraining to attend to the bidimensionality of the cards (Mack, 2007; Ramscar et al., 2013). In Experiment 1A, children played a game prior to the DCCS task that involved matching colors sampled from a wide range of the color dimension used here but that were not the colors used in the DCCS task itself. This experience over the color dimension induced flexible attention switching from shape to color in the DCCS task. A different pattern of results emerged in Experiment 1B. Children did not flexibly switch attention from color to shape in the DCCS task after experience with shapes sampled from the shape dimension. These results mark an important step toward understanding how attention switching can be facilitated across contexts, highlighting the role of stimulus features and how learning carries forward across situations. We discuss these contributions below.

What are the mechanisms by which experience over a dimension might influence attention switching across contexts? It has long been known that memories for auditory and visual features generalize over continuous dimensions based on a similarity gradient (Pavlov, 1927; Spence, 1937; for a discussion, see McLaren & Mackintosh, 2002). An old literature exploring developmental change in children's dimensional attention abilities showed that children's attention could be shifted from the featural to dimensional level by exposing them to multiple values distributed over a dimension, much like we did here. For example, Tighe and Tighe (1969) gave children who were in their first grade of elementary school a cylinder, showed them a series of different sized cylinders, and asked them to judge whether their cylinder matched the one shown to them. This enabled the children to represent relations between previously unseen values along that same size dimension in a transposition task (see also Tighe & Tighe, 1968).

More recently, Perry and Samuelson (2013) induced attention to dimensions in children who were holistic attenders via a categorization task that required attention to a single dimension. In a pretest, children were classified as dimensional or holistic attenders based on performance in a standard triad classification task with stimuli that varied on size and brightness. Children then did a categorization task during which they learned to sort stimuli into two categories based on attention to one dimension, either size or brightness. Children received feedback about their responses and were required to reach a performance criterion of 100% across multiple trials. Perry and Samuelson found that some of the children who had initially been classified as holistic attenders were able to attend dimensionally in a triad classification posttest that followed category learning.

The DNF model provides an account of how experience over a dimension can generate attention at the dimensional level across contexts. The model connects neural populations involved in processing dimensional labels such as "color" and "shape" in the AS to neural populations involved in remembering feature values distributed over those same dimensions in the visual-cognitive system. Experience provided with the label "color" and values distributed over the color dimension during the memory game primed these systems to respond more robustly when exposed to those labels and similar features at a future point in time, as in the DCCS task. Importantly, the experience provided during the memory game led to changes in the activation passed back and forth between the AS and visual-cognitive systems—the same systems responsible for developmental change in dimensional attention in simulations reported by Buss and Spencer (2014). These simulation results raise the possibility that experience with labels and distributed features may be central to developmental changes in dimensional attention.

One alternative explanation of children's enhanced performance in the DCCS task is that the act of matching in the memory game, rather than exposure to the colors, improved children's ability to sort correctly during the DCCS task. Interestingly, the asymmetry in results across Experiments 1A and 1B suggests this alternative is unlikely. In particular, children's performance in the DCCS task when switching from color to shape was not enhanced by the memory-matching game in Experiment 1B, even though children still identified matches.

Critically, results from Experiment 1B also suggest that the metric organization of a dimension influences children's ability to carry forward experiences across contexts and, ultimately, whether or not flexible attention switching can be induced across contexts. Similar asymmetries in children's DCCS performance have been observed in previous studies (e.g., Fisher, 2011). Inspired by simulations of such asymmetries (see Buss & Spencer, 2014), we hypothesized that the shape stimuli used here were metrically compressed—less distinctive—relative to the color stimuli. Simulations of the DNF model demonstrated the viability of this hypothesis—the model effectively captured the full range of children's performance across conditions.

One intriguing possibility raised by these simulations is that the influence of the shape memory game on children's DCCS performance might be enhanced via more intensive experience with the shape dimension. It is well known that the neuronal resources dedicated to stimulus representation can be increased via experience. For example, Recanzone, Merzenich, Jenkins, Grajski, and Dinse

(1992) found that the neural territory devoted to the representation of one finger in somatosensory cortex increases in an experience-dependent fashion in monkeys. Similarly, Ditye et al. (2013) found that improvements in adults' ability to make subtle perceptual discriminations of color–motion conjunctions is associated with increased cortical matter as a result of intensive practice performing discriminations. It is possible that the similarities in the shapes used here, variations in ovals, were compressed relative to the entire shape dimension. The entire shape dimension might reflect children's experience with canonical shapes such as star, triangle, and circle. Giving children extended experience discriminating the shape variations in our stimuli might expand the representational space devoted to variations in oval. This might, in turn, enable experience with shape to induce flexible attention switching from color to shape in the DCCS task. Alternatively, it might be possible to make the shape changes across the dimension more dramatic. While this is conceptually possible, in our stimulus set shapes 1 and 18 are already quite stretched (see Figure 2).

The DNF model provides novel insights into the influence of dimensional experience across contexts. The model has several distinct advantages relative to other neural network models that have been used to capture developmental change in children's performance in the DCCS task (for an extensive comparison of theories, see Buss & Spencer, 2014). For instance, Morton and Munakata (2002) proposed a connectionist model consisting of a bank of nodes for each feature value (e.g., red, blue, circle, star) and a bank of nodes for each label. These input units feed into a hidden layer, which in turn feeds into an output layer that generates a sorting response (left or right). Across a series of trials, a robust latent (long-term) memory develops and competes with an active (working) memory generated by the postswitch sorting cards and labels. Developmental differences in DCCS performance arise when "older" models generate a sufficiently robust active memory for the postswitch rule that can overcome the strength of the latent memory accumulated during the preswitch phase.

The processes in the DNF model involved in children's DCCS performance bear some resemblance to those proposed by Morton and Munakata (2002). For example, competition between memories generated from sorting during the preswitch phase and what the child is asked to sort by in the postswitch phase play an important role in both models' account of young children's performance. But there are also important differences between models that are relevant to the current results (for additional contrasts, see Buss & Spencer, 2014). In particular, the connectionist model represents feature values independent of the dimensions along which they are distributed. Thus, it is unclear how experience with features not present in the DCCS task could influence later sorting as was evident here. The DNF model, by contrast, represents features in neural populations tuned to continuous metric dimensions. This unique feature led to the novel prediction tested in the present study. Further, this aspect of the model was central to our account of why children showed an asymmetry in responding across experiments.

In conclusion, our work highlights the utility of theoretically guided efforts to enhance children's EF abilities. The DNF model led to a key insight about the nature of generalization across contexts, which led to the first empirical demonstration of successful switching by 3-year-old children in the standard DCCS task without simplification or task-specific training. The model provided a mechanistic account of asymmetries in the influence of dimensional experience across contexts as well, highlighting the importance of understanding how the details of the stimulus and task come together to influence children's behavior. The DNF model also inspired a new paradigm for future investigations of how specific types of dimensional experience with features and labels influence young children's cognitive flexibility in the DCCS task. One exciting possibility is that the experience acquired in the memory game might generalize to contexts beyond the DCCS. For example, might experience acquired in the memory game enhance children's working memory for colors?

Perhaps most importantly, our work may shed new light on efforts to train flexible dimensional attention in children. Effective attention switching abilities are necessary for children to meet the challenges they face each day. In the classroom, children are constantly asked to switch attention across dimensions as they shift from one learning context to another. For instance, children must switch from attending to the size dimension while learning mathematics to the color dimension while painting during art. We gave children experience with a dimensional label and stimuli that spanned one metric dimension. The intriguing possibility is that this might be an effective way to help children learn dimensional attention skills as they extract the pattern of associations that maps a dimensional label like "color" to a distributed set of features.

Such training might be an important advance in efforts to foster EFs across a range of contexts, including the out-of-lab contexts so critical to positive developmental outcomes.

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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.** Equations and Parameters