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Autonomy in Action: Linking the Act of Looking to Memory Formation in Infancy via Dynamic Neural Fields

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Abstract

Looking is a fundamental exploratory behavior by which infants acquire knowledge about the world. In theories of infant habituation, however, looking as an exploratory behavior has been deemphasized relative to the reliable nature with which looking indexes active cognitive processing. We present a new theory that connects looking to the dynamics of memory formation and formally implement this theory in a Dynamic Neural Field model that learns autonomously as it actively looks and looks away from a stimulus. We situate this model in a habituation task and illustrate the mechanisms by which looking, encoding, working memory formation, and long-term memory formation give rise to habituation across multiple stimulus and task contexts. We also illustrate how the act of looking and the temporal dynamics of learning affect each other. Finally, we test a new hypothesis about the sources of developmental differences in looking.

Keywords: Dynamic field theory; Dynamic neural field models; Infant looking; Memory formation; Memory development; Embodied cognition

1. Introduction

In seminal theories of cognitive development, early changes in perception, representation, and behavior were grounded in sensorimotor exploration (e.g., rattles are for shaking; Gibson, 1988; Piaget, 1952, 1983; see also Flavell, 1963). The experimental investigation of early cognitive development, however, has largely relied on visual habituation procedures. These procedures are based on the observation that infants' looking time decreases as they are successively presented with a stimulus and recovers if presented with a discriminably different novel stimulus. Indeed, this observation has led to a rich empirical database on the development of basic attentional, perceptual, and memory processes (e.g., Cohen, Gelber, &

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Lazar, 1971; Rose, Feldman, & Jankowski, 2001; Ross-Sheehy, Oakes, & Luck, 2003). Habituation tasks have also been adapted in creative ways to study developmental change in cognitive processes such as statistical learning (e.g., Kirham, Slemmer, & Johnson, 2002; Saffran, Aslin, & Newport, 1996), category formation (e.g., Oakes, Coppage, & Dingel, 1997; Quinn, Eimas, & Rosenkrantz, 1993; Younger & Fearing, 2000), and word learning (e.g., Rost & McMurray, 2009; Werker, Cohen, Lloyd, Cassasola, & Stager, 1998).

Looking is clearly a powerful empirical tool. Nevertheless, many debates are centered on how looking measures should be interpreted. Some researchers have used looking measures to make strong claims about the innate origins of knowledge (Bhatt & Quinn, 2011; see Spelke, 1998 for a discussion), while other researchers have argued that looking measures changes in perceptually based representations over learning (Bogartz, Shinskey, & Speaker, 1997; Cashon & Cohen, 2000; Haith, 1998). Such contradictory interpretations have led many researchers to argue that looking must be more strongly grounded in what is known about basic cognitive processes (see Cohen, 2004; Kagan, 2008; Oakes, 2010; Schöner & Thelen, 2006).

This has been the goal of neural network models. Several formal models have shed light on the neural processes that underlie habituation and led to novel predictions that have been confirmed empirically (French, Mareschal, Mermillod, & Quinn, 2004; Gilmore & Thomas, 2002; Schöner & Thelen, 2006; Sirois & Mareschal, 2004). Although these models constitute a major advance in the field of infant cognition, they all share a common limitation: Looking as an exploratory action has been lost. Instead, these models treat looking behavior as an output of cognitive processing (see Fig. 1A).

Some models, however, have formally treated looking as a dynamic motor act (see Fig. 1B). For example, Robertson, Guckenheimer, Masnick, and Bachner (2004) proposed a stochastic dynamical model and used it to capture¹ the second-to-second dynamics with which 4-week-olds look and look away without any formal contribution of cognitive processing. Looking, of course, is not only a dynamic motor act but also an exploratory behavior by which infants construct knowledge. And several lines of evidence suggest that looking and learning are fundamentally intertwined. For example, experimental manipulations of how infants distribute their looks on the second-to-second time scale affect what infants learn and remember (Jankowski, Rose, & Feldman, 2001). Moreover, how infants distribute their looks when exploring objects is influenced by how other agents manipulate the world. This, in turn, impacts how they explore the world and ultimately the development of cognitive and social abilities (Landry & Chapieskie, 1988; Landry, Smith, Swank, & Guttentag, 2008). To date, formal theories of infant visual habituation have not provided an account of this link between looking and learning.

The goal of this article is to bring together the innovations from the study of infant looking depicted in Fig. 1A and 1B. We propose a new Dynamic Field Theory (DFT) in which looking is one component of a dynamic, exploratory system (see Fig. 1C). Our model explores a virtual world by looking at it, capturing the stochastic nature of looking and looking away. Consequently, what the model sees is driven by what it happens to look at. Looking and learning in our model are interdependent: The length of each fixation depends on the current state of the looking system and the current state of perceptual and memory

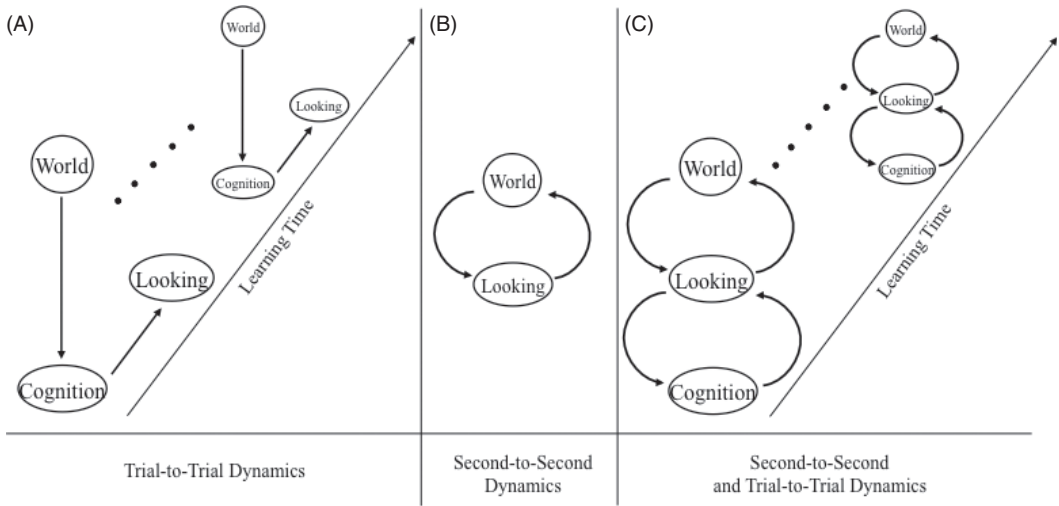


Fig. 1. Three implementations of looking behavior. (A) Looking as a behavioral output of cognitive processing over time. Here, the world is a direct input into the cognitive system and looking a direct index of processing and representation. This system captures the trial-to-trial dynamics of learning. (B) Looking as a stochastic dynamic system that looks at the world. This system captures the second-to-second dynamics of looking and looking away. (C) Puts the concepts in (A) and (B) together to create a dynamic, exploratory system that looks at the world, learns about what is being looked at, which, in turn, contributes to the maintenance and release of fixation. This system integrates the second-to-second dynamics of looking with the trial-to-trial dynamics of learning.

processes. This brings the second-to-second dynamics of looking and the trial-to-trial dynamics of learning together. We discuss how formally implementing the link between looking and learning has consequences for understanding the emergence of cognitive processes in development, and we discuss several novel insights that ground infant cognition in the dynamics of an autonomous, visual exploratory system.

This article is structured around four broad sections. In the first section, we set the stage for our theory and review conceptual and neural network theories of visual habituation. In the second section, we construct our new model and formally establish a link between looking and learning. In the third section, we present a series of simulations that reveal a rich interplay between looking and learning. In the fourth section, we discuss the implications of our theory for the study of infant cognitive development. We also discuss the strengths and weaknesses of our theory that point toward future work.

2. Setting the stage for a new theory

2.1. Conceptual theories of infant habituation

The empirical database from habituation studies has grown immensely over the past several decades, but contemporary thinking about the processes underlying infant habituation is

still strongly influenced by Sokolov's (1963) comparator model. Sokolov proposed that an organism remains oriented toward a stimulus as it constructs an internal representation that matches the stimulus, at which point the organism orients away and seeks novelty. Sokolov's comparator model has been the foundation for later models of habituation. One influential model is Cohen's (1972a,b) dual-process model. This model proposed an *attention-getting* process that controls orienting to a stimulus and an *attention-holding* process that controls sustained looking at a stimulus. Stimulus properties such as brightness and size attract infants' gaze, but, once fixated, perceptual encoding and memory formation sustains fixation. When the infant has formed a memory for a stimulus, the attention-getting process leads the infant to fixate the stimulus, but fixation is not maintained. A central innovation of the dual-process model is that it delineated multiple interactive processes that orient gaze, sustain fixation, and release fixation from a stimulus.

Another influential model of infant habituation is the multifactor model (Hunter & Ames, 1988). A central innovation of this model is that it captures the familiarity-to-novelty shift in infants' visual preferences. The basis of the model is that early in learning, infants actively encode a stimulus, which biases them to preferentially look at familiar over novel stimuli. Late in learning, infants' memory for a stimulus supports recognition and biases them to look at novel over familiar stimuli. The multifactor model assumes that memory formation is gradual and that the time course of this shift varies with the developmental state of the infant and is influenced by contextual factors such as stimulus complexity and the interstimulus interval.

Consistent with the multifactor model, a number of studies have shown that the familiarity-to-novelty shift occurs later for young infants than older infants (e.g., Rose, Gottfried, Melloy-Carminar, & Bridger, 1982). Critically, however, the multifactor model does not specify the mechanisms that underlie this developmental change. This limitation has been partially overcome by the processing speed hypothesis, which posits that infants process visual information more quickly with age. Rose, Feldman, and Jankowski (2002) provided support for this hypothesis. They developed a preferential looking task in which infants were presented with pairs of different stimuli. On each trial, one stimulus remained unchanged (familiar) and one stimulus changed (novel). Processing speed was indexed as the number of trials required to exhibit a novelty preference on three consecutive trials. The number of trials to criterion decreased with age, consistent with increasing processing speed. Nevertheless, questions remain regarding the mechanisms that underlie changes in processing speed. Neural network theories have provided answers to some of these questions. Thus, we turn to these models next.

2.2. Neural network theories of infant habituation

Many classes of neural networks have been used to capture infants' performance in looking tasks (French et al., 2004; Gurekis & Love, 2004; Schöner & Thelen, 2006; Shultz & Cohen, 2004; Sirois & Mareschal, 2004). We focus on three common classes: autoencoders, autoassociators, and dynamic neural fields (DNFs). *Autoencoders* are versatile models that gradually construct an internal representation of a stimulus. Initially, the representation does

not match the stimulus, error is high, and levels of looking are said to be high. Later, the representation can estimate the stimulus, error is low, and levels of looking are said to be low. Autoencoders have made a particularly strong contribution to our understanding of categorization. For example, French et al. (2004) showed that the scope of infants' categories depends on the statistical distribution of feature values to which they are exposed during familiarization.

Like autoencoders, *autoassociators* learn to reproduce an input pattern over trials (see Sirois, 2004 for a review). Sirois and Mareschal (2004) used an autoassociator to construct a model of infant habituation called HAB (for Habituation, Autoassociation, and Brain). A major accomplishment of HAB is that it describes how excitatory and inhibitory neural interactions can impact changes in processing speed over developmental. Moreover, HAB acquires an excitatory long-term memory that, in principle, could influence processing speed upon subsequent encounters with remembered stimuli. Unlike autoencoders, however, HAB has only qualitatively captured a single pattern of data—the familiarity-to-novelty shift. Thus, it is unclear to what extent HAB can elucidate how the stimulus and task context influence learning.

Schöner and Thelen (2006) proposed a DNF model that captured such contextual influences on learning. Their model consisted of coupled excitatory and inhibitory layers. Activity in the excitatory layer generated looking. This feature enabled Schöner and Thelen to capture elevated levels of looking associated with stimulus complexity (e.g., Caron & Caron, 1969) simply by strongly stimulating the excitatory layer. The excitatory layer also generated inhibition, which led to a decline in looking via suppression of the excitatory layer. Moreover, the inherently time-dependent nature of the excitatory and inhibitory dynamics enabled Schöner and Thelen to capture the lack of habituation associated with long interstimulus intervals (e.g., Lewis, 1969). Although compelling, the DNF model provides only limited insight into longer term learning because habituation is driven by an inhibitory memory. Inhibition is certainly involved in habituation; however, looking is also an exploratory behavior by which infants acquire knowledge stored through excitatory memory processes (Sirois & Mareschal, 2004).

In summary, each neural network has made a unique contribution to our understanding of infant cognition. Nevertheless, they all share three limitations that point toward the need for a new theory. The first limitation is that existing theories have not provided an account of the interdependency between looking and learning. Jankowski et al. (2001) eloquently illustrated this linkage across two critical experiments. In the first experiment, they showed that individual differences in looking generalized across stimulus contexts. During a pretest phase, infants were presented with pairs of identical stimuli that consisted of an arrangement of geometrical shapes. The arrangement of shapes naturally segregated into top and bottom portions, which, across the two stimuli, created four quadrants. After the pretest phase, infants were familiarized with a different pair of identical stimuli that also consisted of an arrangement of geometrical shapes segregated into top and bottom portions. Infants who exhibited short looks and frequently switched gaze between the two stimuli during the pretest phase also exhibited a similar style of looking during familiarization. At test, short-looking infants exhibited a novelty preference and

long-looking infants exhibited no preference. In the second experiment, Jankowski et al. (2001) again measured looking during a pretest phase. Now, however, infants who exhibited long looks during the pretest phase were induced to exhibit short looks during familiarization. To induce short looks, a light was illuminated in a different quadrant once every second during familiarization. This experimental manipulation of how infants distribute their looks affected memory formation—long-looking infants now showed a novelty preference at test. Thus, patterns of looking and learning are intertwined. In the theory we present here, we formally implement looking as an active behavior and show that looking matters for learning.

The second limitation shared by existing theories is that they have not captured developmental change in processing speed and discrimination within the same architecture. During the same period that processing speed is increasing, infants exhibit an increased ability to discriminate between highly similar familiar and novel stimuli in visual (Brannon, Sumarga, & Libertus, 2007) and auditory (Lipton & Spelke, 2003) domains. At present, it is unclear whether developmental changes in processing speed and discrimination can arise from a common mechanistic source. We explore this link and show that these changes can indeed arise from the same developmental mechanism.

The last limitation shared by existing theories is that they have not provided an account of the nonlinear tie between looking and memory formation. Conceptual and neural network theories focus on the gradual process of habituation commonly reported in group-level data. At the individual level, however, looking and memory formation have been reported to undergo nonlinear transitions across learning. Roder, Bushnell, and Sasseville (2000; see also Colombo, Mitchell, Coldren, & Atwater, 1990) found that infants transition from exhibiting a familiarity preference to exhibiting a novelty preference as quickly as from one trial to the next. Infants rarely exhibited a null preference in between, a signature of linearly transitioning from encoding to memory. These data are also consistent with Fisher-Thompson and Peterson (2004) who found that infants often transition between familiarity and novelty biases while visually exploring pairs of items. We contend that these observations tell us something new about the learning process in looking tasks, and we show that our theory captures the nonlinear tie between looking and learning.

3. A DFT of infant looking and memory formation

The DFT is a theory of embodied cognitive dynamics (for a review, see Spencer, Perone, & Johnson, 2009). This theory falls within the theoretical umbrella of dynamic systems theory (for a discussion, see Spencer & Schöner, 2003). Dynamic systems theory construes behavior as an emergent product of self-organizing, multicomponent systems interacting over multiple time scales (Simmering & Perone, unpublished data; Spencer, Perone, & Buss, 2011; Thelen & Smith, 1994). One challenge for systems theories in psychological sciences has been to concretely apply these concepts to explain how neurocognitive and action systems work together to create the specific behaviors observed and studied in the laboratory. The DFT has emerged as one solution to this challenge. In particular, this

framework uses dynamical neural networks called DNFs to explain how behavioral patterns arise from neural population dynamics coupled to sensorimotor systems.

The theory and DNF model we propose is connected to a larger set of concepts examining the real-time integration of brain and behavior over learning and development (for reviews, see Schöner, 2009; Spencer et al., 2009; Spencer, Simmering, Schutte, & Schöner, 2007). DNFs have provided an account of the mapping between real-time neural dynamics and behavior (Kopecz & Schöner, 1995; Wilimzig, Schneider, & Schöner, 2006), the planning of reaching movements (Bastian, Schöner, & Riehle, 2003), working memory for visual features (Johnson, Spencer, Luck, & Schöner, 2009; Johnson, Spencer, & Schöner, 2009), and spatial working memory (see Spencer et al., 2007 for a review). DNFs have also been used to explain the codevelopment of neural and behavioral processes in the Piagetian A-not-B task (Thelen, Schöner, Scheier, & Smith, 2001) and spatial working memory tasks (Schutte & Spencer, 2009; Schutte, Spencer, & Schöner, 2003; Simmering, Schutte, & Spencer, 2007).

The starting point for our theory is a DFT of visual working memory and change detection in adults proposed by Johnson et al. (2009). We chose this starting point because it enables us to probe whether there is developmental continuity in basic visual cognitive processes. Johnson et al. proposed that visual recognition and change detection arise from the real-time interaction between perceptual and working memory processes. In their DNF model, multiple items (e.g., colored squares) are encoded in parallel. Encoding generates a working memory representation that can be actively maintained in the absence of input. The maintenance of items in working memory, in turn, inhibits encoding of remembered stimulus values. Consequently, when old items are re-presented in the task space, they are inhibited from building a new perceptual representation—the system recognizes them as “known.” In contrast, new items have stimulus values that fall outside the range of inhibition. This causes a new perceptual representation to form and the system detects the novelty. Here, we generalize this model to infant habituation by adding a form of Hebbian learning (see Lipinski, Simmering, Johnson, & Spencer, 2010; Lipinski & Spencer, 2010; Spencer, Dineva, & Schöner, 2009). This enables the system to respond more robustly to previously encoded items and facilitates working memory formation across trials.

We also added a stochastic fixation system which determines when stimulus values enter the perceptual and working memory system as the fixation system looks and looks away from stimuli. Our implementation is based on work by Robertson et al. (2004) who proposed a simple dynamical systems model to capture the exploratory dynamics of looking in infancy. The model consisted of a single bistable unit that, when above threshold (zero), was said to be “looking” and, when below threshold, was said to be “looking away.” Noise and a small bias to enter the looking state produced a stochastic, oscillatory pattern of looking and looking away. This simple model captured the looking dynamics of 4-week-olds situated in front of an array of toys, including the transition rate between looking and looking away, look duration, and look away duration. The stochastic oscillatory dynamics of looking and looking away may be a general property of exploratory behavior that impact learning. For instance, Mobus and Fisher (1999) proposed that an animal situated in an unfamiliar environment needs an efficient, timely exploratory strategy to discover relevant

features of the environment. They found that a robot that oscillated stochastically between left and right movement directions more efficiently discovered and learned about spatial locations at which reinforcement was given than a robot that explored the space randomly.

In the sections that follow, we construct our model in four parts. First, we describe the general concepts that underlie DNFs. Second, we describe our adaptation of the Johnson et al. (2009) model. Third, we describe our adaptation of the Robertson et al. (2004) fixation system. Finally, we couple these systems together and illustrate how the integrated system looks and learns in a habituation task.

3.1. Central concepts of DNFs

A DNF consist of layers of neurons organized by functional topography along continuous, metric dimensions (e.g., color). In DNFs, neighboring/similarly tuned neurons mutually excite each other and inhibit dissimilarly tuned neurons (see Bastian et al., 2003; Georgopoulos & Massey, 1988; Spencer et al., 2009). This type of neural interaction creates a local excitatory/lateral inhibitory activation profile, a ubiquitous form of neural interaction in the nervous system that stabilizes motor behavior and neural representations within the cognitive system (Fuster, 2003). Neuronal activation in DNFs evolves continuously in time, and the state of a DNF at any point in time depends on its own intrinsic dynamics, the inputs impinging on them, and previous states the DNF has entered. Neuronal layers in DNFs are a lower level representation of a high dimensional space and emphasize the neural attractor states that these layers enter. Amari (1977) originally analyzed five qualitatively different attractor states that DNFs can enter. Below, we describe three of those states and their cognitive function in the context of infant habituation (see Spencer et al., 2009 for a review).

The first attractor state is the *resting* state in which neuronal activation rests at a baseline level of activity. Our account of infant habituation is largely centered on transitions into and out of the resting state and two additional attractor states, the *self-stabilized* and *self-sustaining* states. When a stimulus is present, DNFs can enter a self-stabilized state in which neurons create a localized peak of activity, a real-time neural representation of the stimulus at the level of the neural population. This peak must be stabilized by the continued presence of input; once the input is no longer available, the peak subsides and the system moves back into the resting state. In previous work, we have used the self-stabilized state to capture the dynamics of perceptual encoding where perceptual representations are distributed along continuous spatial and featural dimensions (e.g., Johnson et al., 2009).

DNFs can also enter a self-sustaining state in which recurrent local excitatory connections are sufficiently strong to maintain peaks in the absence of stimulation. We have used this attractor state to capture the active maintenance of items in working memory (Johnson et al., 2009; Schutte & Spencer, 2009; Simmering, 2008; for related models, see Compte, Brunel, Goldman-Rakic, & Wang, 2000; Edin, Macoveanu, Olesen, Tegner, & Klingberg, 2007). The neural dynamics of the self-sustaining state are consistent with findings showing that neurons exhibit sustained and elevated levels of discharge during delays (Funahashi, Bruce, & Goldman-Rakic, 1989).

Fig. 2 illustrates these two neural attractor states and how Hebbian learning can modulate these states. Across panels A–E, a stimulus (see top row) is presented to an excitatory layer of neurons which we will refer to as a perceptual field (PF). When neurons in this excitatory layer are stimulated by input (B), they stimulate neighboring neurons (blue arrow). Above-threshold (>0) neurons also stimulate neurons in an inhibitory layer (Inhib; not shown for simplicity). When these inhibitory neurons become active, they project inhibition back to the excitatory layer (red arrow). Recurrent interactions between PF and Inhib create a localized peak of activation (B). Notice that once the input is removed, the field returns to its resting level (C). Above-threshold peaks leave an activation trace in a Hebbian layer (H_{PF}), which feeds back into PF. Functionally, this strengthens the connections among previously excited neural sites in PF. The contribution of H_{PF} to PF is shown by the light gray bump of activation at the bottom of Fig. 2B (right y-axis). As can be seen in Fig. 2D, this contribution strengthens the neural response upon subsequent presentations of the stimulus.

When the excitatory and inhibitory layers interact more strongly (i.e., stronger local excitation/lateral inhibition) and there is support from the Hebbian layer, DNFs can enter a self-sustaining state. This is illustrated in the bottom row of Fig. 2. Across panels F–J, the stimulus shown in the top row is presented to an excitatory layer of neurons as before. Now,

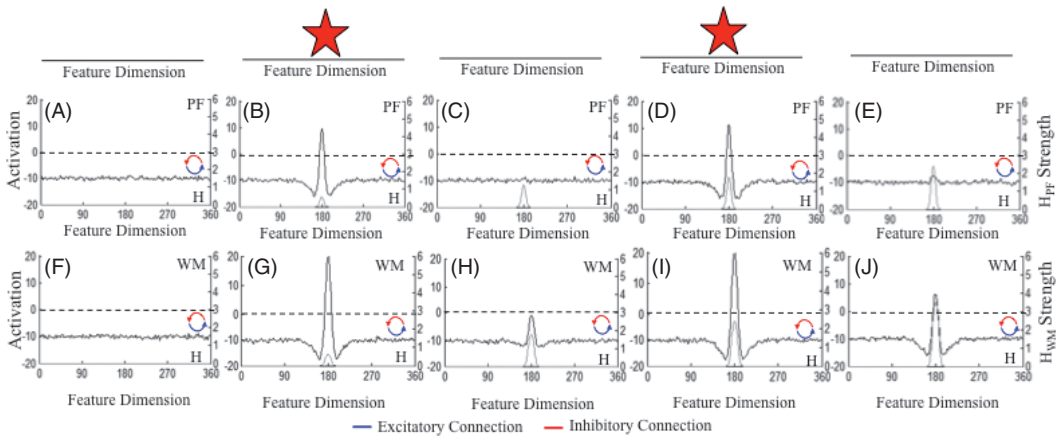


Fig. 2. Middle row illustrates the self-stabilized state in PF and its mapping to perceptual encoding. Initially, no stimulus is present (see top row) and PF is in the resting state (A). There is no contribution of H_{PF} to PF (gray line, right y-axis). The presence of Hebbian learning within a layer is denoted by H. When a stimulus is present, interactions between PF and Inhib (red and blue loop) create a self-stabilized peak and activation in H_{PF} accumulates (B). When the stimulus is removed, PF returns to the resting state (C). The contribution of H_{PF} to PF strengthens activation in PF (D). Functionally, H_{PF} primes PF to encode recently encoded stimuli. When the stimulus is removed once again, activation in PF returns to the resting state (E). Bottom row illustrates the self-sustaining state in WM and its mapping to working memory. Initially, no stimulus is present and WM is in the resting state (F) and there is no contribution of H_{WM} . When a stimulus is present, interactions between WM and Inhib (red and blue loop) create a self-stabilized peak and activation in H_{WM} accumulates (G). When the stimulus is removed, WM returns to the resting state (H). When the stimulus is re-presented (I), the contribution of H_{WM} to WM strengthens activation in WM and enables it to maintain a self-sustaining peak in the absence of input (J).

however, we have labeled the field “working memory” (WM) to reflect the stronger neural interactions. Initially, no stimulus is present and WM is in the resting state (F). When a stimulus is presented, WM enters the self-stabilized state (G), and, as before, activation returns to its resting level when the stimulus is removed (H). When the stimulus is re-presented, however, WM enters the self-sustaining state: A peak of activation is built that is dynamically stable in (J) even though the stimulus is no longer present—the stronger interactions in WM enable this field to actively maintain the item in memory.

3.2. *Adaptation of the Johnson et al. (2009) architecture: The three-layer+ model²*

Johnson and colleagues (2009) proposed a three-layer DNF model that was able to recognize and detect novelty by comparing items in memory with incoming perceptual information. Our central thesis is that the same neural mechanisms underlying visual recognition and change detection in adults underlie visual recognition and habituation in infancy, with one central difference: Visual recognition in infancy unfolds more gradually through time, and learning processes play a stronger role in the formation of visual preferences in infancy. The basic concepts behind our thesis are shown in Fig. 3. This figure shows a simulation of the three-layer architecture from Johnson et al. (2009) with Hebbian layers (H_{PF} and H_{WM}) added to both excitatory fields. The second row shows a PF (A–E) with relatively weak neural interactions, and the bottom row shows a working memory field (WM; F–J) with stronger neural interactions. As in Johnson et al. (2009), input (see top row) is passed strongly into PF and weakly into WM. Above-threshold activation in PF stimulates similarly tuned excitatory neurons in WM (blue arrow from PF to WM). Both PF and WM are coupled to a shared layer of inhibitory interneurons (Inhib), which is not shown for simplicity. The inhibitory projections to PF and WM are shown by the red bidirectional arrow. (Note that because PF projects strong excitation to WM, there is little net inhibitory influence of PF on WM in the simulations reported here. For an alternative example, see Schutte & Spencer, 2009.) Finally, the contribution of H_{PF} and H_{WM} to activation within the excitatory layers is shown in light gray (see right y-axis).

When a stimulus is presented to the three-layer+ model, a self-stabilized peak arises in PF and excitation is propagated into WM (Fig. 3A). When the stimulus is removed, a WM peak maintains a representation of the stimulus in its absence (B). Note that the maintenance of a WM peak inhibits associated neurons in PF via the shared layer of inhibitory interneurons (see red-dashed arrow). When an identical stimulus to the item held in WM is presented, activation in PF is relatively weak (compare A with C). This suppression of encoding is the neural basis of visual recognition in our model. In contrast, when a novel stimulus is presented (see the shift in input along the feature dimension in D), it excites uninhibited neurons in PF and a robust peak emerges (D). This strong neural signal is the basis of novelty detection in our model. Note that these mechanisms of recognition and novelty detection resemble data showing that neural responses decline with stimulus repetition (Desimone & Duncan, 1995; Snyder, 2007).

Below, we provide a more detailed overview of the three-layer+ model. Where necessary, we provide details on model parameters. Additional model parameters are reported in Table 2.

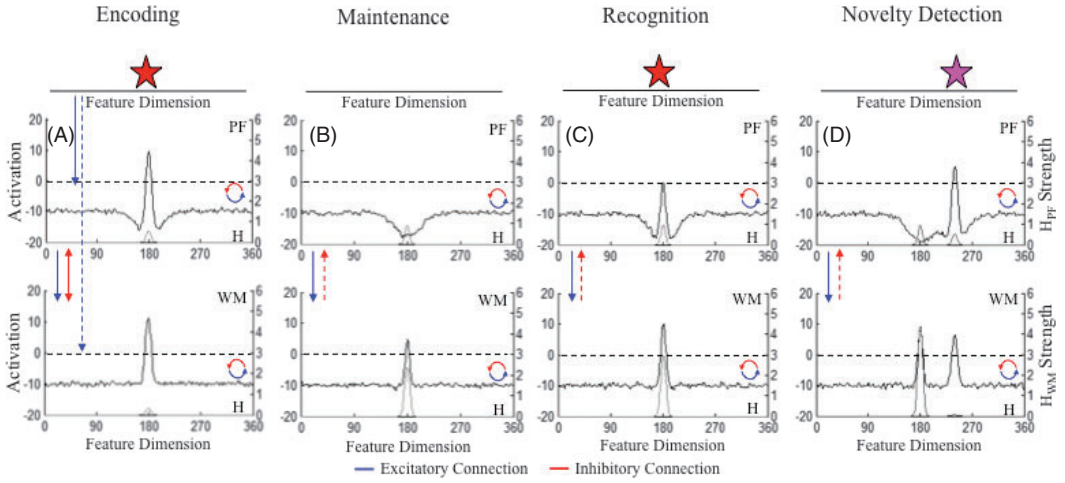


Fig. 3. (A) Connectivity of three-layer+ architecture. The stimulus (top row) is input strongly into PF (solid blue arrow) and weakly into WM (dashed blue arrow). Local excitatory/lateral inhibitory interactions between PF and Inhib and WM and Inhib are shown by blue and red loops within each layer. PF passes strong excitation to WM (solid blue arrow), and, via Inhib, PF passes inhibition to WM and WM passes inhibition to PF (red bidirectional arrow). For simplicity, remaining panels and figures do not show input connection. Remaining panels also do not show bidirectional inhibition between PF and WM. Instead, we show a dashed inhibitory arrow from WM to PF to highlight the strong tuning from WM to PF that, functionally, inhibits activity in PF. (A–D) How perceptual encoding in PF and working memory formation coexist in the three-layer+ model. When a stimulus is presented, activation in PF encodes the stimulus and feeds into WM (A). When the stimulus is removed, WM is tuned such that it is able to sustain a peak in the absence of stimulus or PF input (B). Note that inhibition in PF is strong, which arises from the contribution of WM to PF via Inhib (red dotted arrow). This suppresses further encoding upon subsequent encounters with an identical stimulus (C), the mechanism of recognition in the model. When a novel stimulus is presented, it excites uninhibited neurons in PF; activation is strong and begins to update WM (D). This is the mechanism of novelty detection in the model.

3.2.1. Perceptual field

The PF consists of reciprocally coupled excitatory, $PF(u)$, and inhibitory, $Inhib(v)$, layers. The excitatory layer of PF is given by the following equation:

$$\begin{aligned}
 \tau_{excite}\dot{u}(x, t) = & -u(x, t) + h_u + S(x, t) \\
 & + \int c_{uu}(x - x')\Lambda_{uu}(u(x', t))dx' \\
 & - \int c_{uv}(x - x')\Lambda_{uv}(v(x', t))dx' \\
 & + \int c_{uhl}(x, x')hl_u(x, t)dx' \\
 & + N(x, t)
 \end{aligned} \tag{1}$$

where $\dot{u}(x, t)$ is the rate of change of activation across the continuous behavioral dimension (e.g., color), x , as a function of time, t . τ_{excite} is the time constant along which excitatory

activation evolves, which was fixed at 80 for all simulations. Activation at each site within the excitatory layer is influenced by several factors including its current state, $-u(x,t)$, its negative neuronal resting level, h_u , and input, $S(x,t)$, such as the presentation of a stimulus at a central location. Input takes the form of a Gaussian distributed over the behavioral dimension, x :

$$S(x, t) = c \exp \left[-\frac{(x - x_{center})^2}{2\sigma^2} \right] X(t) \quad (2)$$

with its position centered at x_{center} , width σ , and strength c . For all simulations, σ was fixed at 3 and, except where noted, c was fixed at 17. The gating function, $X(t)$, denotes that the stimulus input is weighted with a 1 during time intervals when the stimulus is present and 0 otherwise. These timing parameters are dictated by the details of the experimental paradigms we simulated, where 1 time step in the model = 10 ms.

The neural dynamics within PF are also influenced by excitatory within-layer neural interactions, $\int c_{uu}(x - x') A_{uu}(u(x', t)) dx'$. These interactions are specified by the convolution of a Gaussian local excitation profile, $c_{uu}(x - x')$ [equation 2 without the gating function, $X(t)$], which determines the neighborhood across which excitatory interactions propagate, and a nonlinear sigmoidal threshold function, $\Lambda_{uu}(u(x', t))$, which dictates that only neurons with above-threshold activation (>0) participate in the locally excitatory interactions. The sigmoidal function is specified by:

$$\Lambda(u) = \frac{1}{1 + \exp[-\beta u]}, \quad (3)$$

where β is the slope of the sigmoid. β was set to .05 for all simulations.

In addition to local excitatory interactions, the neural dynamics in PF are influenced by inhibition, $-\int c_{uv}(x - x') A_{uv}(v(x', t)) dx'$. This inhibition is generated by the activity of neurons in an inhibitory layer (v) [see equation 5 below]. As with excitatory interactions, inhibitory interactions in PF are projected across a neural neighborhood specified by a Gaussian, $c_{uv}(x - x')$, and only neurons with above-threshold activity in the inhibitory layer, $A_{uv}(v(x', t))$, contribute to interactions.

Next, neurons in PF are influenced by input from a Hebbian layer (H_{PF} ; see equation 7 below), $\int c_{uhl}(x, x') h_l(v(x', t)) dx'$. This input is determined by the convolution of a Gaussian projection, $c_{uhl}(x, x')$, which specifies the neural neighborhood across which Hebbian learning has an influence. In all simulations, the spread of the projection from H_{PF} to PF, σ_{uhl} , was fixed at 3, and the strength, c , was fixed at .7.

The final contribution to activation dynamics within PF is the addition of spatially correlated *noise*:

$$+N(x, t) = q \int g_n(x - x') \xi(x', t) dx' \quad (4)$$

Noise is presented to the excitatory layer by convolving a field of white noise, $\xi(x', t)$, with a Gaussian kernel, $g_n(x-x')$. For all simulations, the spread of the noise kernel, σ_{noise} , was fixed at 1 and, except where noted, the strength of noise, q , was fixed at .12.

3.2.2. Inhibitory field (Inhib)

The excitatory layer of PF is reciprocally coupled to an inhibitory layer, Inhib (v). The equation for the inhibitory layer is

$$\begin{aligned} \tau_{inhib}\dot{v}(x, t) = & -v(x, t) + h_v \\ & + \int c_{vu}(x - x')\Lambda_{vu}(u(x', t))dx' \\ & + \int c_{vw}(x - x')\Lambda_{vw}(w(x', t))dx' \\ & + N(x, t) \end{aligned} \quad (5)$$

where $\dot{v}(x, t)$ specifies the rate of change of activation for each inhibitory neuron, x , as a function of time, t , which is influenced by its current state, $-v(x, t)$, and its resting level, h_v . The time constant, τ_{inhib} , of the inhibitory layer was fixed at 10 for all simulations. The inhibitory layer receives excitatory inputs from both PF, $\int c_{vu}(x - x')\Lambda_{vu}(u(x', t))dx'$, and WM, $\int c_{vw}(x - x')\Lambda_{vw}(w(x', t))dx'$. These inputs are projected across a neural neighborhood specified by each Gaussian projection, $c(x - x')$, and only above-threshold neurons in PF and WM contribute to these cross-layer interactions as determined by the sigmoidal threshold function, Λ . Finally, an independent source of spatially correlated noise is added to the inhibitory layer (see equation 4).

3.2.3. Working memory field (WM)

The excitatory layer of the WM(w) field is specified by the following equation:

$$\begin{aligned} \tau_{excite}\dot{w}(x, t) = & -w(x, t) + h_w + cS(x, t) \\ & + \int c_{ww}(x - x')\Lambda_{ww}(w(x', t))dx' \\ & - \int c_{wv}(x - x')\Lambda_{wv}(v(x', t))dx' \\ & + \int c_{whl}(x, x')hl_w(v(x, t))dx' \\ & + \int c_{wu}(x - x')\Lambda_{wu}(u(x', t))dx' \\ & + N(x, t) \end{aligned} \quad (6)$$

This equation is identical to the equation for PF (see equation 1) with the following exceptions. First, the input, $S(x, t)$, is weighted by a strength parameter, c , which was set to 0.05 for all simulations. Second, WM receives an excitatory projection from

$PF(u), \int c_{wu}(x - x')\Lambda_{wu}(u(x', t))dx'$, given by the convolution of a Gaussian projection and the sigmoidal threshold function. For all simulations, the spread of the projection from H_{WM} to WM , σ_{whl} , was fixed at 3, and the strength, c , was fixed at .31.

3.2.4. Hebbian layers (H)

Activation within PF and WM is influenced by traces in associated Hebbian layers. The equation for the Hebbian layer associated with PF is

$$hl'_u(x, t) = \begin{cases} \frac{1}{\tau_{build}}[-hl_u(x, t) + \Lambda_u(u(x, t))] & \text{if } u(x, t) \geq 0 \\ \frac{1}{\tau_{decay}}[-hl_u(x, t)] & \text{otherwise} \end{cases} \quad (7)$$

where $hl'_u(x, t)$ is the rate of change of activation for each site in the Hebbian layer, x , as a function of time, t . The constants τ_{build} and τ_{decay} set the time scale during which activation traces accrue and decay, respectively. Activation in H_{PF} accrues at specific sites, x , when the activation of a given neuron in PF is above threshold, $u(x, t) \geq 0$. τ_{build} was set to 10,000, and τ_{decay} was set to 50,000. The input to H_{PF} at each site is simply the thresholded activation of each above-threshold neuron in PF, $\Lambda_u(u(x, t))$.

3.3. Adaptation of the Robertson et al. (2004) fixation system

The three-layer+ model specifies the perceptual, working memory, and learning processes hypothesized to underlie visual habituation and discrimination in infancy. The next step is to specify the process that underlies fixation dynamics in infancy. For this, we adapted the model from Robertson et al. (2004). The fixation system consists of a single dynamical node that looks at and looks away from a center location in the task space at which a stimulus can appear (see Fig. 4). The behavior of the fixation system over time is determined by its own intrinsic dynamics and noisy inputs impinging on it. The fixation system is given by the following equation:

$$\tau_{excite}\dot{f}(t) = -f + h_f + c_{ff}\Lambda_f(f) + c_{boost} + c_{static} \quad (8)$$

where the time scale of the activation variable, f , is set by the constant, τ_{excite} . The rate at which activation in the fixation system changes is influenced by its current state, $-f$, and its negative neuronal resting level, h_f [see equation 9 below]. The fixation system has a self-excitatory component that creates bistable switching between an “off” state and an “on” state over time. This nonlinear behavior is mediated by a sigmoidal threshold function, $\Lambda_f(f)$, which is weighted by a self-excitatory gain parameter, c_{ff} . In addition, the fixation system receives two inputs: c_{boost} , a strong, transient input or “attention getter” that when present quickly moves the fixation system from a negative “off” state to a positive “on” state, and c_{static} , a low-level input that signals the presence of a stimulus at a center location. At every time step, white noise was added to c_{static} (see Fig. 4B).

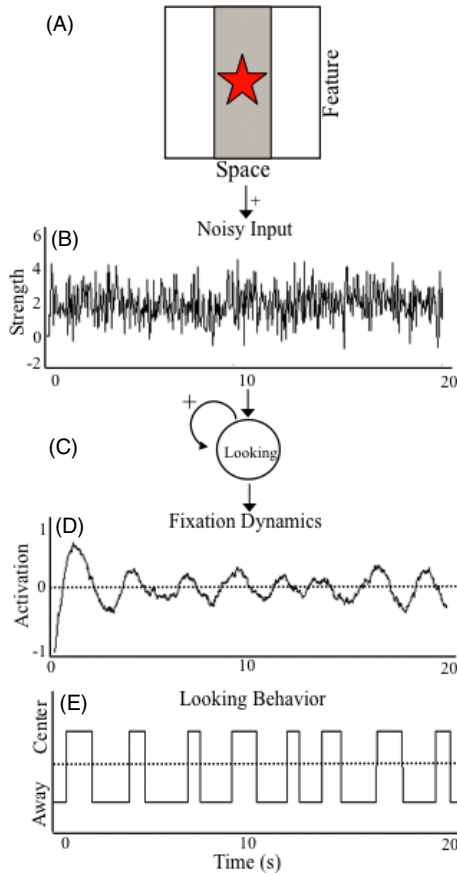


Fig. 4. The architecture and behavior of the fixation system across a 20-s period. The fixation system looks and looks away from a single location in space at which a stimulus sampled from a single feature dimension is present (A). When a stimulus is present at a center location, it presents noisy input to the fixation system (B). The combination of a self-excitatory connection within the fixation system and presence of noisy input (C) can bias the fixation system to enter and sustain above-threshold (i.e., above 0) activation. These inputs, together with the resting-level dynamics (see text), create a stochastic oscillation between the looking and looking away state (D) and variable look durations across time (E).

The final contribution to the fixation system comes from a dynamic resting level which facilitates transitions between “on” and “off” states. The resting level of the fixation system, h_f is governed by the following equation:

$$\tau_{excite}\dot{h}(t) = -h_f + h_{rest} + h_{down}\Lambda_f(f) \tag{9}$$

The resting level of the fixation system decreases toward a low attractor, h_{down} , when the current activation of the fixation system is above threshold, and it moves toward the baseline level, h_{rest} , when activation in the fixation system is below threshold. Thus, the fixation

system is biased toward the “off” state when in the “on” state, and it is biased toward the “on” state when in the “off” state. This implements a type of bias similar to that used by Robertson et al. (2004), helping to create a stochastic, oscillatory pattern of looking (“on”) and looking away (“off”) through time. The fixation system parameters used in the simulations are presented in Table 2.

Fig. 4 shows the behavior of the fixation system over a 20-s period. Fig. 4A shows the presence of a stimulus at a center location in the task space and the noisy input (B) it presents to the fixation system (C). Initially, there is no input and the fixation system is at its resting level (D) and looking away (E). In habituation experiments, there is commonly an attention getter (e.g., periodic blinking light) at the location a stimulus will appear. We approximate an attention-getting stimulus with a strong, transient input (c_{boost}) to the fixation system (see initial spike in B). This drives activation in the fixation system to an above-threshold looking state quickly. Note, however, that the attention getter is not required for the system to acquire the looking state. When a stimulus is present on the display (e.g., within a trial), a noisy low-level input is also presented to the fixation system signaling the presence of a stimulus at a center location. The combination of the continuous presence of a low-level input and the self-excitatory dynamics of the fixation system bias the system to remain in the looking state. However, noise and resting-level modulation (see equation 9) can spontaneously drive the fixation system to a looking away state or, if in the looking away state, to a looking state. To calculate discrete looks, we required the fixation system to sustain suprathreshold activation for more than 25 time steps, eliminating brief threshold crossings as potential looks that sometimes occurred when the fixation system was transitioning from one state to the other (e.g., see Fig. 4D at approximately 5 s).

As can be seen in Fig. 4, these dynamics enable the fixation system to stochastically oscillate between looking and looking away (D), producing fixations of variable duration (E). These dynamics resemble the behavior of the system used by Robertson et al. (2004) and the exploratory dynamics of some robotic systems (Mobus & Fisher, 1999). Note that there are some differences between our fixation system and the one used by Robertson et al. First, noise within our system is introduced via noisy input, whereas noise in their system was intrinsic. These types of noise differ only during the interstimulus interval when no task-relevant input is present in the task space. We used the current noise model based on previous work using noisy inputs to capture infants’ spontaneous reaching behavior in the Piagetian A-not-B task which depends on available input sources (Dineva, Schöner, & Thelen, 2010). Second, hysteresis within our system is created by self-excitatory dynamics, when entering the looking state, and resting-level dynamics, when entering the looking away state. In Robertson et al.’s model, hysteresis was introduced with a small bias to remain in the recently entered state.

3.4. Autonomous looking and learning: The integrated architecture

In our theory, looking behavior, perceptual processes, and working memory processes are inseparable components of an integrated autonomous, exploratory system that learns as it looks. We constructed this system by coupling the fixation system to the three-layer+ model.

First, we specified the coupling from the fixation system to the three-layer+ model. We wanted fixation to act as a perceptual gate, allowing input to the three-layer+ model only when the system was in the looking state. To achieve this, we modified the inputs to PF (see $S(x,t)$ in equation 1) and WM (equation 6) by gating these inputs by the thresholded activation of the fixation system, that is, $S(x,t)$ was replaced by $S(x,t)A(f)$.

Next, we specified the coupling from the three-layer+ model into the fixation system. Conceptually, we wanted the formation of a perceptual representation in PF (i.e., a peak) to feedback onto the fixation system and support continued looking. To implement this integration, we modified equation 8 as follows:

$$\tau_{excite}\dot{f}(t) = -f + \dots\Lambda_f(f) \int c_{fu}\Lambda_u(u(x',t))dx' \quad (10)$$

where $\int c_{fu}\Lambda_u(u(x',t))dx'$ is the weighted sum of above-threshold activation in PF across all sites, x , at time, t . This term is weighted by the thresholded activation of the fixation system, $\Lambda_f(f)$, which ensures neural activity in PF only contributes to the fixation system when in the looking state.

Fig. 5 illustrates how the DNF model learns autonomously as it explores a stimulus over time. At the top is a single stimulus in the task space (A). The next panel shows the behavior of the fixation system (B) over the course of a 200-s simulation. Initially, the model exhibits several long bouts of looking as the fixation system maintains above-threshold activation (C). Over time, look durations become increasingly shorter as the fixation system pierces threshold, enters the looking state, but quickly looks away.

The neural dynamics within PF and WM at different points during familiarization (30 s, 40 s, 88 s, 96 s, and 160 s) are shown in Fig. 5D–5H. Fig. 5D shows the state of PF and WM as well as the Hebbian layer contributions (gray lines, right y-axis) as the model looks at the stimulus early in learning. Activation in PF is strong, activation has started to form a weak peak in WM, and the H contributions are just beginning to emerge. The peak in PF helps support the long look by the fixation system around 30 s (C). Fig. 5E shows the state of PF and WM while the model is looking away early in learning (at 40 s). Activation in PF and WM has returned to subthreshold levels after the fixation system spontaneously looked away. Note that there are modest contributions from the Hebbian layers at neural sites associated with the stimulus.

As the model continues to explore the stimulus, the contribution of H_{WM} to WM increases (F) and a stable WM peak emerges. Consequently, when the model looks away from the stimulus at 96 s (G), the peak is maintained, inhibiting associated sites in PF (see circled inhibitory trough in PF in panel G). This inhibition suppresses the formation of a peak in PF when the model looks at the stimulus again late in learning at 160 s (H). This suppression of encoding quickly releases fixation, look durations become short, and the model accumulates more time looking away. Thus, the model habituates to the stimulus.

3.5. Overview of model simulations

In the following sections, we situated our autonomous DNF model in a habituation task. We focused on the single presentation variant because it highlights the complex interplay

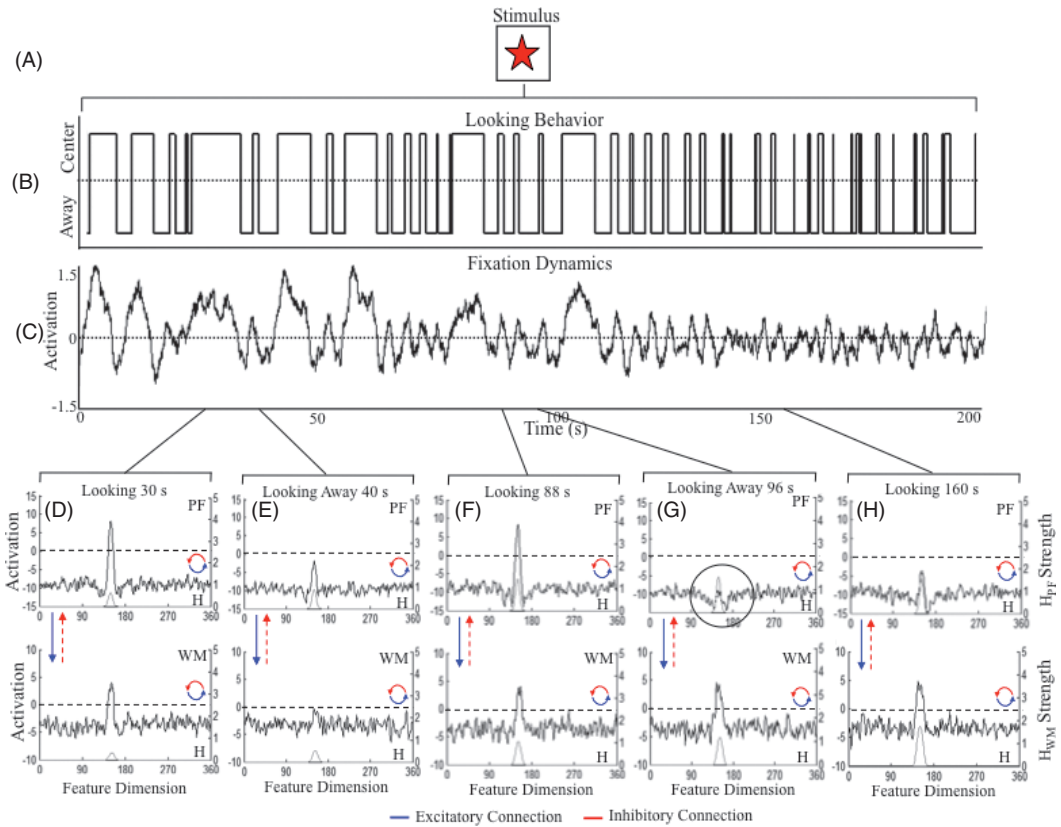


Fig. 5. Processes by which a dynamic exploratory system autonomously learns by looking. (A) Single stimulus in the task space. (B) Duration of looking and looking away from the stimulus across 200 s of exploration. (C) Fixation dynamics that are directly translated into looking and looking away. Early in learning, the model exhibits few looks that are of long duration. Late in learning, the model exhibits many looks that are of short duration. This pattern of looking arises from the model encoding the stimulus early (D and E), which supports looking, and the emergence of a stable working memory late (F–H), which suppresses encoding and leads to the rapid release of fixation.

between looking and learning even in the simplest of paradigms. We will present 24 sets of simulation results. Results from each simulation set were based on 200 simulations of the same model for a total of 4,800 simulations. Simulation of the model with a given parameter setting produces variable behavioral patterns (see Fig. 9). Calculating the mean and standard deviation across small batches of simulations yields estimates of the model's performance that can fluctuate, much like fluctuations in infants' data with small sample sizes. To ensure that the results reported here were robust across batches of simulations, we conducted preliminary simulation work. These efforts demonstrated that 200 simulations per set produced replicable, stable results (e.g., means were quantitatively close across repeated batches of 200 simulations from the same experimental condition). Except where noted, trial durations were 20 s and interstimulus intervals were 5 s.

In the simulations below, there were three stimulus inputs. One input was the habituation stimulus, centered at site 150 in a field consisting of 360 neurons. The other two stimuli were test stimuli: a *close* test that differed from the habituation stimulus by 20 neurons (site 170) and a *far* test that differed from the habituation stimulus by 40 neurons (site 190). The close and far tests allow us to test whether developmental change in processing speed and discrimination can arise from the same mechanism.

Unless noted, simulations were conducted with a single set of parameters to illustrate the basic concepts of our theory. We refer to these parameters as our standard or young infant model. Parameters for the young infant model were fit by hand to qualitatively match the slow habituation, long looks, and generalization of habituated levels of looking to novel stimuli highly similar to the habituation stimulus. We tested the set of parameters across all conditions in which the young infant model was situated in, modifying parameters to qualitatively capture all behavioral patterns. Next, we tested whether developmental change in looking and discrimination could be captured by manipulating only the excitatory/inhibitory connection strength within PF and WM. These parameter manipulations were chosen based on previous work using a similar model architecture to capture developmental change in children's performance in a spatial working memory task (Schutte & Spencer, 2009).

We present simulation results across six sections. Table 1 provides an overview of these simulations, highlighting the model process emphasized by each simulation and the concepts illustrated. In *Mechanisms of infant habituation*, we show how perceptual, working memory, and long-term memory processes are integrated over learning. We illustrate how the unfolding of these processes leads to habituation of looking to a single stimulus as well as novelty detection and dishabituation. In *Mechanisms of developmental change*, we focus on the global excitatory and inhibitory neural interactions in the model and test whether the Spatial Precision Hypothesis (SPH)—which specifies global changes in the strength of these neural interactions over development—can capture developmental differences in habituation and dishabituation. In *Autonomy and emergent individual differences*, we emphasize the coupling between looking and learning and illustrate how that coupling enables a single system to produce variability in performance through time that can lead to faster or slower learning. In *Comparison of DNF model with Schöner and Thelen (2006)*, we show how our neural model responds to the stimulus strength and timing manipulations explored in Schöner and Thelen's model and compare these two dynamical models of infant habituation. We also test whether the SPH can capture a familiarity-to-novelty shift that occurs over just a few weeks very early in development. This set of simulations illustrates that our model can quantitatively capture infant behavior. Finally, we illustrate how excitatory long-term memory processes capture differences in looking to stimuli with varying levels of familiarity. In *Are learning and development the same thing?*, we contrast global differences in the strength of excitatory/inhibitory dynamics with locally specific long-term memory. In *Looking matters for learning*, we illustrate how direct experimental manipulations of looking in the model impact learning. See Appendix for additional simulations of the infant-control paradigm.

The simulations below largely focus on qualitative comparisons between the model's behavior and patterns of infant looking over development. We focused on qualitative patterns

for two reasons. First, the central goal of this article is to present a general theoretical account of visual habituation; thus, we emphasize the pattern of results across a host of studies, rather than any one result in isolation. If the same model with the same parameters can produce the right qualitative pattern across simulation sets, that is a robust way to assess the generality of the model. Second, infant habituation studies on a given topic vary widely in methodological detail. Nevertheless, there are often robust commonalities in infants' performance across studies. Consider three studies on stimulus complexity. To manipulate complexity, each investigation manipulated the number of checks within a checkerboard. Caron and Caron (1969) presented infants with a single checkerboard across five 20-s trials sandwiched between four trials on which a different stimulus was presented; Greenberg, O'Donnell, and Crawford (1973) successively presented infants with three different checkerboards across twelve 30-s trials; Cohen, Deloache, and Rissman (1975) presented infants with a single checkerboard across 16 infant-controlled trials sandwiched between two trials on which a different stimulus was presented. Despite these methodological variations, infants across studies exhibited more looking time to more complex checkerboards than less complex checkerboards.

Importantly, methodological variation can also meaningfully impact looking behavior. For this reason, a theory must be able to capture quantitative patterns of behavior. This can elucidate how a cognitive and behavioral system organizes itself within a specific task context. Thus, we also present a set of quantitative simulations showing our theory is up to this challenge.

4. Mechanisms of infant habituation

In this section, we describe the mechanisms of habituation and dishabituation when our standard young infant model is situated in a habituation task. We illustrate how looking is linked to the processes of encoding and memory formation over the course of habituation. We then illustrate the mechanisms underlying generalization of looking and dishabituation to novel stimuli.

4.1. Habituation

Fig. 6 illustrates how looking is linked to encoding and working memory formation over the course of habituation. When the model looks on trial 1, PF activity is strong and the model begins to form a WM peak (A). Strong PF activity supports looking, leading to few looks, long look durations, and high levels of total looking time. Encoding and working memory formation during trial 1 also accumulates activation in H_{PF} and H_{WM} , respectively (gray line, right y-axis). During the ISI following trial 1 (B), H_{PF} is stronger than H_{WM} , which facilitates further encoding of the stimulus on trial 2.

As the model explores the stimulus across trials, WM activity is strengthened via the continued accumulation of activation in H_{WM} (C–D). This leads to stronger suppression of associated sites in PF, which is evident by trial 7 (see circled inhibitory trough around stimulus site 150 in panel F). Consequently, PF provides weaker support for fixation over trials, and

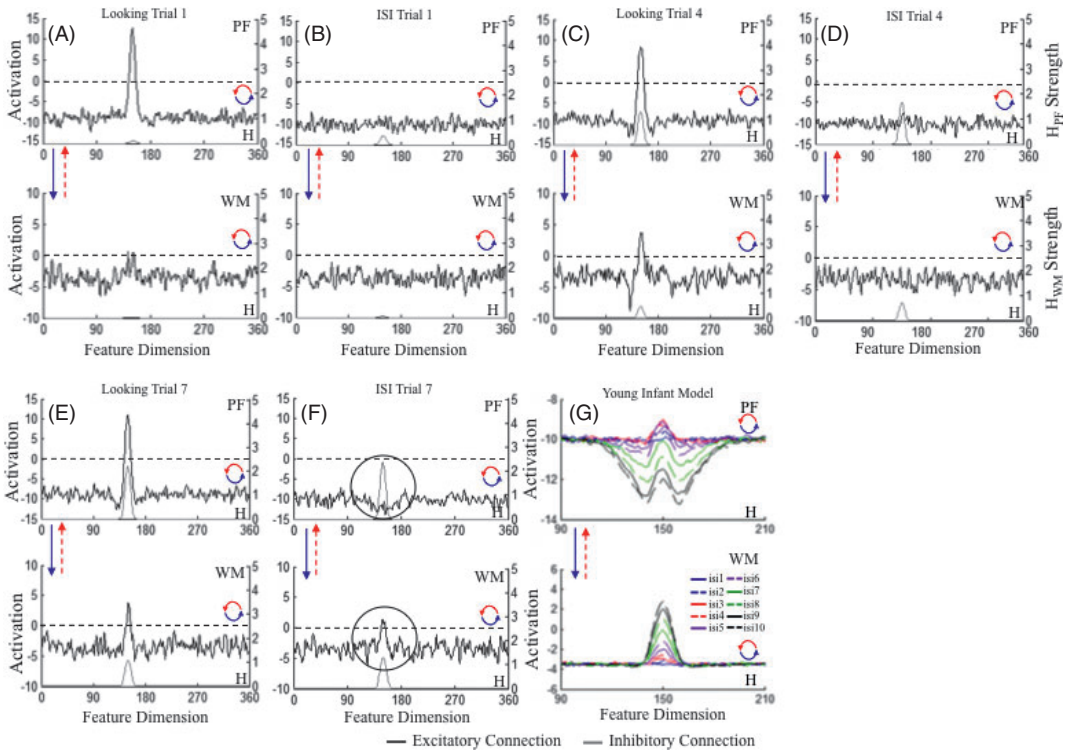


Fig. 6. The state of PF and WM in the standard (young infant) model across the habituation phase. Early in learning, the model encodes and begins to form a working memory, and accumulates a long-term memory (gray line, right y-axis) for the stimulus as it looks and looks away (A–D). Late in learning, the model establishes a stable WM peak for the stimulus, which suppresses encoding and leads to looking away (E and F). (G) Activation profile of the young infant model at the onset of each habituation trial. The activation profile is the state of PF and WM averaged across simulations.

PF encodes the stimulus for increasingly shorter durations. This causes look durations and looking time to decrease over trials. At the same time, Hebbian traces facilitate stable WM peak formation, enabling the system to maintain a representation of the stimulus in the absence of input. For instance, there is a WM peak in the bottom panel of Fig. 6F, even though no stimulus is present during the ISI.

Fig. 6G shows the mean state of PF and WM across the entire simulation set (i.e., 200 simulations) at the onset of each habituation trial (i.e., the end of each interstimulus interval). When the model begins each trial early in learning, the contribution of H_{PF} to PF facilitates encoding (see positive activation in PF early in learning in the top panel of G). Late in learning, H_{WM} accumulates and a stable WM peak emerges and produces strong inhibition in PF. Consequently, when the model begins successive trials late in learning, the stimulus excites strongly inhibited neurons in PF and activity is weak. Habituation, then, arises from a transition in the model from encoding early in learning to the active maintenance and recognition of the habituation stimulus late in learning. This transition can be seen in the

Table 1
Simulation overview

Section	Simulation	Model Process	Illustration
1	Mechanisms of habituation		
	Habituation	Integration of fixation dynamics with perceptual, working memory, and long-term memory processes over learning	Habituation of looking
	Dishabituation	Fast release from fixation when item matches working memory; renewed support for fixation from perceptual processing otherwise	Novelty detection, generalization, and discrimination
2	Mechanisms of developmental change		
	Developmental differences	Global modulation of excitatory/inhibitory neural interaction strengths over development	Test Spatial Precision Hypothesis of developmental change in looking, memory, and discrimination
	Autonomy and individual differences		
	Autonomy and emergent individual differences	Coupled looking and learning means that random fluctuations early in learning can lead to different learning profiles	Differences in learning rates across simulations with the same parameters due to autonomous looking
3	Comparison of DNF model to Schöner and Thelen (2006)		
	Stimulus strength	Vary input strength	Captures insights from Schöner and Thelen regarding how inputs affect habituation
	Interstimulus interval	Vary timing of events	Captures insights from Schöner and Thelen about how timing influences habituation
	Capturing familiarity and novelty over development	Global changes in excitatory/inhibitory dynamics captures familiarity and novelty effects	Familiarity-to-novelty shift over development and quantitative simulations of early development
	Integration of learning with real-time process	Integration of working and long-term memory over delays	Delayed recognition
4	Are learning and development the same thing?		
	Are learning and development the same thing?	Modulate long-term memory strengths relative to global excitatory/inhibitory strengths	Distinguishing long-term memory from Spatial Precision Hypothesis
5	Looking matters for learning		
	Looking matters for learning	Coupled looking and learning	Direct experimental manipulation of looking

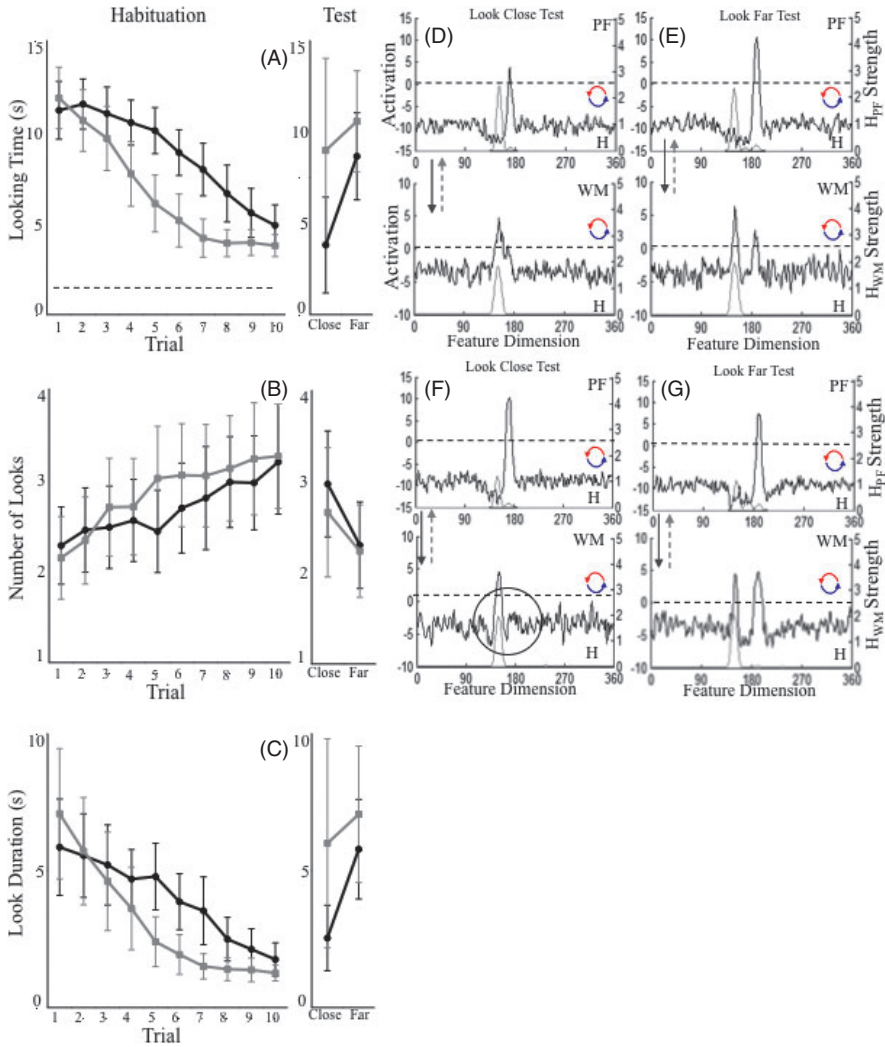


Fig. 7. The looking behavior of the young infant model (black lines and circles) and old infant model (gray lines and squares) during the habituation and test phases averaged across simulations. Error bars are 1 SD. The young infant model is slower to exhibit a decline in looking (A), exhibits fewer looks (B), and exhibits longer look durations (C) across trials than the old infant model. The young infant model exhibits an increase in looking time to the far test, but not the close test, relative to the last habituation trial. The old infant model exhibits an increase in looking time to both the close and far tests. Mechanisms of generalization of looking (D) and dishabituation (E) in the young infant model. When the model looks at the close test, the stimulus excites strongly inhibited neurons in PF that is arising from the stable WM peak. Activation in PF is weak and provides little support for the fixation system. The model generalizes habituation levels of looking. When the model looks at the far test, the stimulus excites uninhibited neurons in PF. Activation is strong and able to sustain above-threshold levels, supporting looking, and giving rise to dishabituation. (F and G) Mechanisms underlying discrimination between the habituation and close test in the old infant model. When the model looks at the close test, the strong excitatory connections in PF and lateral inhibition in WM enables activation in PF produced by the close test to be sustained and support looking (F). The mechanism of dishabituation to the far test is comparable to the young infant model (G).

activation profile between trials 6 (dashed purple line) and 7 (solid green line) when, on average, the model acquires a stable WM peak and inhibition in PF becomes relatively strong.

The looking behavior of the young infant model across simulations is shown in Fig. 7 (black lines). Across simulations, the model exhibited relatively high levels of total looking time early in habituation and slowly transitioned to low levels of looking time late (A). Decreases in looking time across trials happen as the model more frequently looks and looks away (B) and look durations become shorter (C). This arises from the accumulation of activation in WM and H_{WM} and, ultimately, the emergence of a stable WM peak that suppresses encoding and releases fixation. Although few studies report looking dynamics across trials, these looking dynamics are consistent with empirical findings showing that infants exhibit more, shorter looks over learning (Clearfield & Fisher Thompson, 2009; Pancratz & Cohen, 1970; Ruff, 1975). In the DNF model, such dynamics are meaningfully linked to memory formation. We elaborate on this below (see ‘‘Autonomy and Emergent Individual Differences’’).

4.2. Dishabituation

Looking time to novel stimuli following the habituation phase is most often the behavioral measure of interest in habituation studies. In the DNF model, dishabituation happens when a novel stimulus excites neurons in PF to above-threshold levels and this activation is sustained long enough to support continued looking by the fixation system. Critically, whether this occurs depends on the magnitude of inhibition in PF created by a stable WM peak. The looking behavior of the young infant model to metrically similar (close) and metrically dissimilar (far) test items is shown in Fig. 7A (black line). As can be seen in the figure, the young infant model exhibits habituated levels of looking to the close test but elevated looking to the far test; the young infant model generalizes its WM representation to the similar, novel item but shows a discrimination response to the dissimilar item.

Fig. 7D and 7E illustrates the mechanisms underlying these behaviors. This figure shows the state of PF and WM when the young infant model is looking at the close (D) and far (E) test. When the model looks at the close test, the stimulus excites neurons in PF that are strongly inhibited by the stable WM peak associated with the habituation stimulus (see lower panel of D). Thus, the novel stimulus builds a relatively weak peak in PF, and this field provides little support to the fixation system, and looking time does not exceed habituated levels. When the model looks at the far test stimulus, in contrast, the stimulus excites relatively uninhibited neurons in PF (E). Thus, strong PF activity ensues, which provides strong excitatory input to the fixation system and supports continued looking.

In summary, when our autonomous exploratory system is situated in a habituation task, it exhibits long looking early as it encodes a stimulus and forms a memory. It exhibits a decrease in looking late as it forms a stable WM peak associated with the stimulus, which suppresses further encoding, and, in turn, releases fixation. Dishabituation occurs in the model when a new stimulus is presented that re-ignites a peak in the PF.

5. Mechanisms of developmental change

Across the first year, infants habituate more rapidly, exhibit shorter look durations, and switch gaze more frequently (for a review, see Colombo & Mitchell, 1990). These behavioral changes have been attributed to increases in processing speed. Across the first year, infants also exhibit an enhanced ability to discriminate between highly similar familiar and novel stimuli (Brannon et al., 2007). These findings have been attributed to change in the precision with which infants remember visual stimuli. Recall that existing theories of infant visual habituation have not tested whether these developmental changes arise from a common mechanistic source. Here, we show that an increase in the strength of excitatory and inhibitory interactions in our model captures both developmental phenomena simultaneously.

Our implementation of changes in neural interaction was guided by the SPH proposed by Schutte, Spencer, and colleagues (Schutte & Spencer, 2009; Schutte et al., 2003; Simmering et al., 2008). The SPH posits that excitatory and inhibitory neural interactions become stronger over development as children accumulate experience across diverse contexts. Such increases in neural interaction strength are a likely outcome of general Hebbian processes as the same neural system is activated across time and situations. Interestingly, stronger neural interactions do not simply increase the efficiency of neural processes; they also lead to more precise neural representations as seen in work examining developmental changes in children's spatial recall performance (Schutte & Spencer, 2009) and position discrimination (Simmering et al., 2008).

Here, we implement the SPH and test whether it captures developmental changes in infant habituation and discrimination. To create an old infant model, we implemented the SPH on our standard, young infant model. In particular, we increased the strength of local excitatory connections in PF (c_{uu}) and WM (c_{ww}), and we increased the strength of the inhibitory projection from Inhib to PF (c_{uv}) and Inhib to WM (c_{wv} ; see Schutte & Spencer, 2009). The parameter settings for the old infant model can be seen in Table 2.

The neural dynamics underlying the looking behavior of the old infant model are shown in Fig. 8. As can be seen in panels A and B, the old infant model is comparable to the young infant model at the start of habituation. Note, however, that the old infant model has a stable WM peak during the ISI of trial 4 (see lower panel in D), and by trial 7, this WM peak suppresses activity in PF when the model looks at the stimulus (E). Fig. 8G shows the distribution of activation in PF and WM at the start of each habituation trial across the simulation set (for ease of comparison to the young infant model, we have reproduced Fig. 6G in panel H). As can be seen, the old infant model first formed a stable WM peak earlier in habituation than the young infant model, producing inhibition in PF quite early. Moreover, the old infant model builds a more robust—and sharper—WM peak by the end of learning, with strong local excitation and noticeable surround inhibition (Fig. 8G, lower panel). This is an emergent consequence of stronger cross-layer interactions between WM and Inhib. Strong neural interactions mean that there is a sharper gradient at the left and right edge of the peak. Consequently, fewer neurons participate in the locally excitatory interactions (Schutte & Spencer, 2009; for related ideas see Schutte et al., 2003).

The effect of these neural dynamics on the looking profile during habituation and test is shown in Fig. 7 (gray lines). The early formation of a strong, stable WM peak leads to sup-

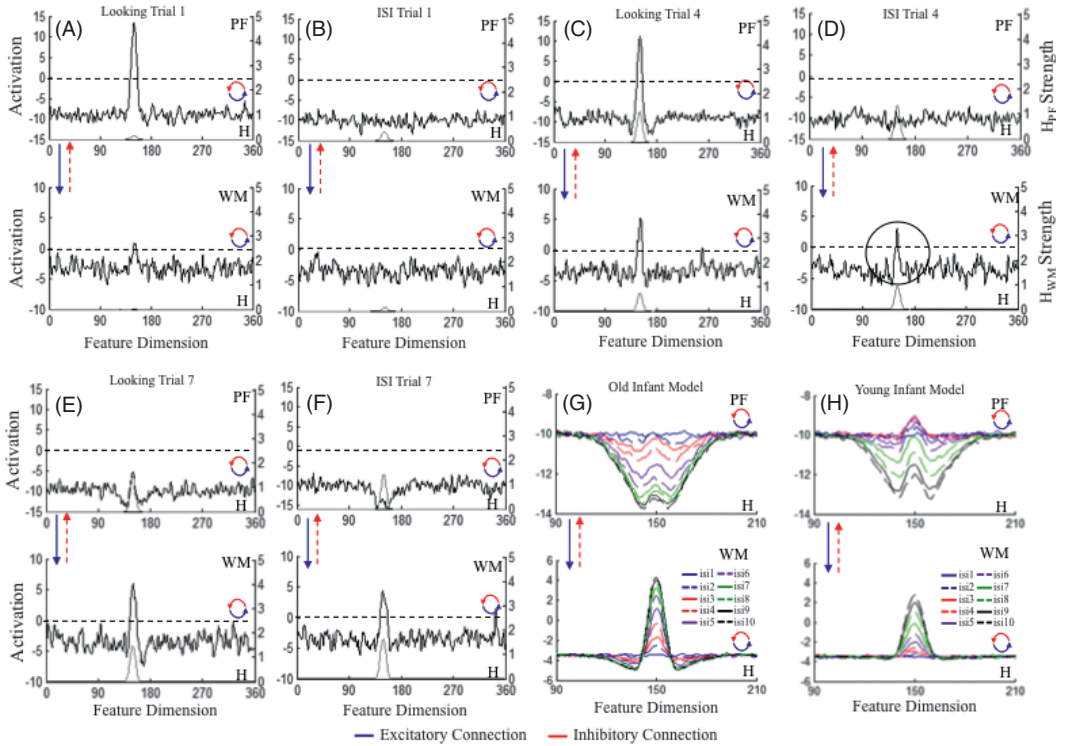


Fig. 8. The state of PF and WM in the old infant model across the habituation phase. Like the young infant model, early in learning the model encodes, begins to form a working memory, and accumulates a long-term memory (gray line, right y-axis) for the stimulus as it looks and looks away (A–D). However, the old infant model establishes a stable WM peak more rapidly. In this example, the model acquired a stable WM peak by trial 4, which produces strong inhibition in PF via Inhib across the remaining habituation trials and, behaviorally, low levels of looking time. For comparison, the activation profile of the young (G) and old (H) infant models at the onset of each habituation trial are shown side by side. The strong excitatory and inhibitory interactions of the old infant model enable it to encode and form a working memory more quickly than the young infant model. In addition, the strong interactions of the old infant model lead to a sharpened WM peak with strong lateral inhibition.

pression of PF activity early. This, in turn, leads to a faster decline in looking time over trials (A), a faster rise in the number of looks (B), and a steeper decline in look durations relative to the young infant model (C). Thus, the old infant model shows the looking profile associated with faster processing speed in the infant literature.

The neural dynamics for the old infant model also influence discrimination. As shown in Fig. 7A, this model dishabituates to both the close and far test. This enhanced discrimination performance emerges from the stronger neural interactions in the old infant model as shown in Fig. 7F. When the old infant model looks at the close test, this stimulus excites neurons in PF that are near the region inhibited by the WM peak. Nevertheless, because the close stimulus is near—but distinct from—the location of the sustained WM peak, the system updates the WM representation and builds a new WM peak at the site of the close stimulus value (see cir-

Table 2 Model parameters

	Young Infant	Old Infant	Wetherford and Cohen (1973)			
			6 Weeks	8 Weeks	10 Weeks	12 Weeks
Fixation(<i>f</i>)						
h_{rest}	-5	-	-	-	-	-
h_{down}	-2.5	-	-	-	-	-
c_{ff}	1.2	-	1.07	1.13	1.2	1.2
c_{fu}	0.15	-	0.137	0.144	0.15	0.15
c_{uf}	1	-	-	-	-	-
PF(<i>u</i>)						
h_u	-10	-	-	-	-	-
c_{uu}	0.693	0.791	0.035	0.329	0.42	0.497
σ_{uu}	3	-	-	-	-	-
Inhib(<i>v</i>)						
h_v	-10	-	-	-	-	-
c_{uv}	0.239	0.265	0.255	0.255	0.255	0.357
σ_{uv}	15	-	-	-	-	-
c_{vu}	0.8	-	-	-	-	-
σ_{vu}	5	-	-	-	-	-
c_{vw}	3.2	-	-	-	-	-
σ_{vw}	5	-	-	-	-	-
c_{wv}	0.023	0.136	0.0025	0.0025	0.02	0.0625
σ_{wv}	15	-	-	-	-	-
WM(<i>w</i>)						
h_w	-3.5	-	-	-	-	-
c_{ww}	0.771	1.232	0.2067	0.2385	0.7791	1.0494
σ_{ww}	3	-	-	-	-	-
c_{wu}	0.15	-	-	-	-	-
σ_{wu}	5	-	-	-	-	-

cled region in the lower panel of Fig. 7F). The updating of WM takes time which enables PF to support continued fixation of the test stimulus, leading to looking times that exceed habituated levels. The mechanism underlying discrimination between the habituation stimulus and the far test is comparable to the young infant model (see Fig. 7G). Here, stronger excitatory connections within PF tend to sustain above-threshold activation while a WM peak is forming (see lower panel). This helps PF support longer looks to the far test stimulus.

In summary, simulations in this section demonstrate that the SPH yields both an increase in processing speed over development *and* enhanced discrimination. The SPH was initially proposed as an account of developmental changes in 2- to 6-year-olds' memory for spatial locations. The fact that the SPH captures developmental changes in looking behavior in infancy is remarkable.

6. Autonomy and emergent individual differences

Recall that one limitation shared by existing theories of infant habituation is that they have not accounted for the interdependency between looking and learning. Moreover, they

have not accounted for the nonlinear tie between looking and memory formation. Here, we show that implementing looking as an active behavior overcomes these limitations. Additionally, we show that the interdependency between looking and learning and the nonlinear tie between looking and memory formation are, in fact, related.

The canonical habituation curve shown in Fig. 7 arises from the model's dynamics specified by the parameter settings; however, embedded within this curve are simulation-to-simu-

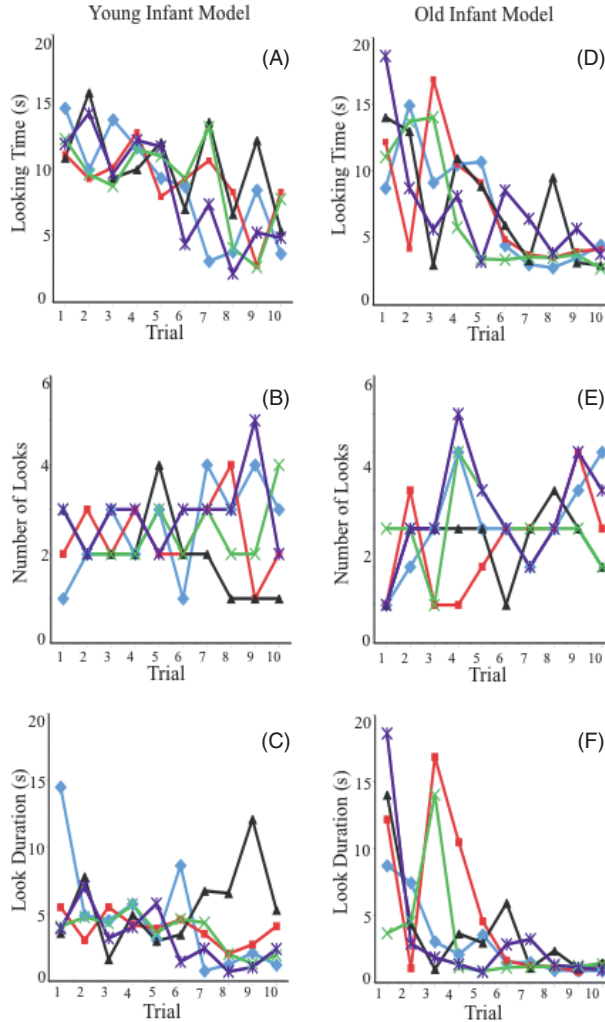


Fig. 9. A sample of the looking time, number of looks, and look duration during the habituation and test phase from five simulations of the young (A–C) and old (D–F) infant models are shown. Each line color is the behavior of a different simulation. The looking behavior of the model fluctuates across trials and simulations. Across simulations, both models exhibit a decline in looking time across trials, an increase in the number of looks, and a decrease in look duration. Across the sample simulations, the old infant model exhibits a more rapid decline in looking time than the young infant model, which is associated with a steeper incline in the number of looks and decline in look duration across trials.

lation variations. Fig. 9 shows sample simulations of the young (A–C) and old (D–F) infant models for three indices of performance during habituation. These individual simulations show rather striking differences in the model’s performance across simulation runs. Critically, this variation is not random; rather, there is underlying structure (see also Aks, Zelinksky, & Sprott, 2002). A central contributor to this structure is variance in the time course of stable WM peak formation. As we show next, the formation of a stable WM peak is a nonlinear event that occurs over learning as WM transitions from the self-stabilized (input driven) to self-sustaining (maintenance) state. Critically, the formation of a self-sustaining WM peak has a significant, nonlinear impact on looking.

Fig. 10 shows the distribution of trials on which a stable WM peak was first formed across the 200 simulations for the young and old infant models. Our criterion for the onset of a stable WM peak was the trial during which a peak remained above-threshold for the duration of the ISI. Both sets of simulations show dramatic variation in the onset of stable WM peak formation across simulation runs, even though all simulations at a given age used exactly the same model parameters. What factors determine which simulations learn quickly and which simulations learn more slowly? As discussed previously, the DNF model brings together the second-to-second dynamics of looking with the trial-to-trial dynamics of learning. Critically, the pattern of looking through time affects the emergence of a stable WM peak, just as the emergence of a stable WM peak affects the pattern of looking through time.

To show the interdependence between looking and learning, we selected a set of simulations with an early onset of stable WM peak formation and a set of simulations that showed a late onset for both the young infant model (trials 5 and 8, respectively) and the old infant model (trials 2 and 5, respectively). Next, we anchored our three behavioral

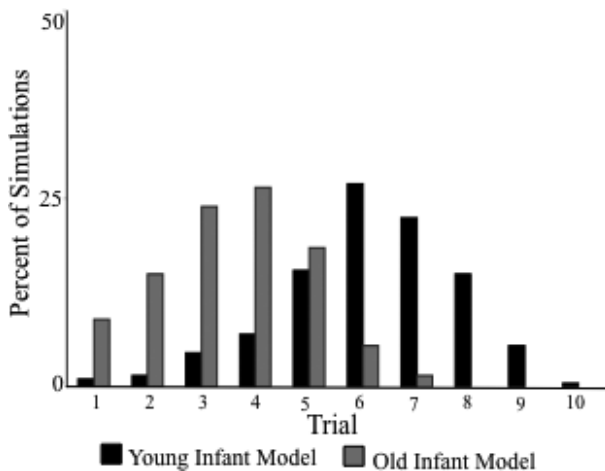


Fig. 10. The distribution of trials on which a stable WM peak first emerged across simulations. The young infant model tended to form a stable WM peak on trials 5–8, whereas the old infant model tended to form a stable WM peak on trials 2–5. These differences in the rate at which the young infant and old infant models form a stable WM peak are attributable to the SPH.

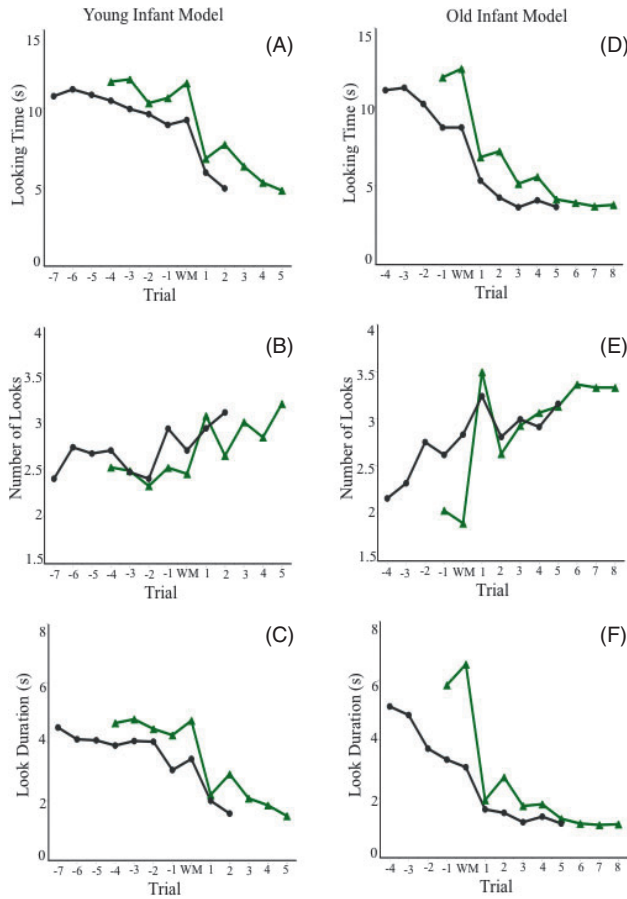


Fig. 11. Highlights the linkage between looking and the time course of stable WM peak formation. The looking behavior of the young infant and old infant models is anchored to the trial on which a stable WM peak was formed. (A–C) Looking time, number of looks, and look duration of the young infant model for simulations that acquired a peak on trials 5 (green lines and triangles) and 8 (gray lines and circles). (D–F) Same looking measures for the old infant model for simulations that acquired a peak on trials 2 (green lines and triangles) and 5 (gray lines and circles). In both models, high levels of looking, few looks, and long look durations early in learning were associated with stable WM peak formation earlier than low levels of looking, many looks, and short look durations early in learning. The formation of a stable WM peak also gave rise to behavioral signatures of memory formation, including a dramatic decline in looking, increase in the number of looks, and decrease in look duration. For simplicity, error bars are not shown. SD (in s) for the young infant model that formed a stable WM peak on trial 5 during the first block of three trials was 3.01, 2.85, and 2.80; SD for the young infant model that formed a stable WM peak on trial 8 during the first block of three trials was 3.51, 2.73, and 2.76; SD for the young infant model that formed a stable WM peak on trial 5 during the last block of three trials was 2.77, 2.64, and 2.44; SD for the young infant model that formed a stable WM peak on trial 8 during the last block of three trials was 2.89, 2.50, and 1.96. SD for the old infant model that formed a stable WM peak on trial 2 during the first block of three trials was 4.01, 3.46, and 3.31; SD for the old infant model that formed a stable WM peak on trial 5 during the first block of three trials was 3.09, 2.63, and 2.79; SD for the old infant model that formed a stable WM peak on trial 2 during the last block of three trials was 1.18, 1.10, 1.05; SD for the young infant model that formed a stable WM peak on trial 5 during the last block of three trials was 1.50, 1.78, and 1.31.

measures of the model's performance to the trial of WM formation. Fig. 11A–11C shows the looking behavior of the young infant model for early-onset (green line) and late-onset (gray line) simulations. Late-onset simulations exhibited relatively low levels of looking time, a high number of looks, and short look durations early in habituation. This pattern of looking slows perceptual encoding and memory formation. In contrast, early-onset simulations exhibited relatively high levels of looking time, few looks, and long look durations early in habituation. These looking dynamics facilitate encoding and memory formation early in learning.

The old infant model exhibits very similar behavior. Fig. 11D–11F shows the looking behavior of the old infant model for early-onset (green line) and late-onset (gray line) simulations. Late-onset simulations exhibited low levels of looking, a high number of looks, and short look durations early in habituation. Early-onset simulations, in contrast, exhibited high levels of looking, few looks, and long look durations early in habituation. Note that these differences in looking dynamics were evident on the very first trial—they reflect initial, random fluctuations in the fixation and neural systems. These initial fluctuations cascade into meaningful changes in looking and learning over trials. In addition, the emergence of a stable WM peak has a nonlinear impact on looking. Notice the sharp decline in looking time, sharp increase in the number of looks, and sharp decrease in look duration once a stable WM peak emerges in Fig. 11.

These simulations illustrate that looking and learning are interdependent in the DNF model. This interdependence emerges from integration of processes operating over multiple time scales. The second-to-second dynamics of fixation, for example, impact the evolution of real-time neural activation. This, in turn, impacts the slower dynamics of LTM formation which reciprocally influences WM formation. And ultimately, these WM dynamics feedback on the second-to-second dynamics of looking. The behavior of the system we are studying, then, reflects the self-organization of multiple processes evolving on multiple time scales (for related concepts, see Ihlen & Vereijken, 2010; Holden, Van Orden, & Turvey, 2009).

7. Comparison of DNF model to Schöner and Thelen (2006)

Schöner and Thelen (2006) used a DNF model to capture infant visual habituation. We wanted to probe the resemblance between our model and theirs by testing whether our model retains two central innovations of the Schöner and Thelen model: (1) looking and learning in their model was influenced by the stimulus and task context; (2) their model was able to capture a familiarity preference in single presentation tasks. We show that our model retains these innovations. We also probe the contribution of a key difference between models. In particular, the Schöner and Thelen model habituated via an inhibitory memory. Our model, in contrast, habituates via an excitatory memory. We show that this enables our model to specify how a long-term learning history impacts looking and learning in real-time.

7.1. Stimulus strength

Infants exhibit elevated levels of looking to complex stimuli (Brown, 1974; Caron & Caron, 1969; Cohen et al., 1975; Greenberg et al., 1973) and, in some cases, more quickly learn about stimuli that are dynamic (Horst, Oakes, & Madole, 2005; Robinson & Sloutsky, 2004). One hypothesis for these findings is that complex and dynamic stimuli recruit and require more information processing resources. In DNFs, the strength of activation is an index of the processing of stimuli (Schöner, 2009), which is influenced by stimulus strength. To illustrate this concept, Schöner and Thelen (2006) showed that intense stimulation produced more looking time across trials but, interestingly, did not affect habituation rate.

In our DNF model, strong stimulation produces similar results. Fig. 12 shows the looking time (A) and distribution of trials on which a stable WM peak was formed (B) for the standard, young infant model when the stimulus strength was increased from 17 (black line) to 19 (blue line). Stronger stimulation led to an overall increase in looking time but no dramatic change in habituation rate. The model also formed a stable WM peak earlier when strength was increased to 19 (blue bars). Although a stable WM peak emerges early in habituation, looking time does not show a sharp decrease over trials because strong excitation in PF counteracts the inhibitory contribution from WM. We also tested the model with a weaker stimulus of strength 15, which led to low levels of looking (green line in A) and a

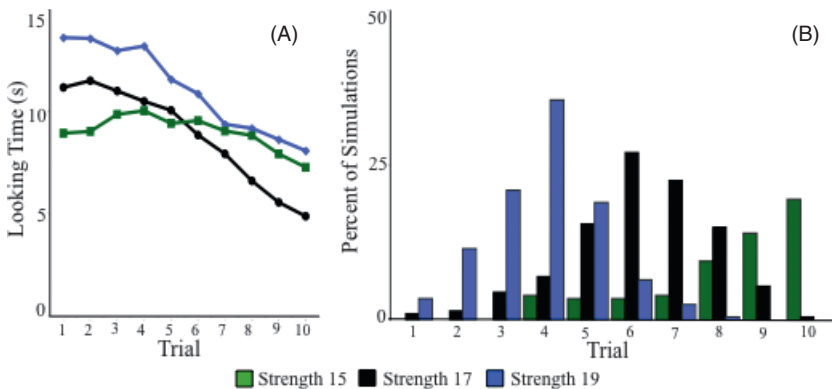


Fig. 12. The looking time (A) and distribution of trials on which a stable WM peak was formed (B) for the standard (young infant) model presented with three different stimulus strengths. When the stimulus strength was increased from 17 (black line and circles) to 19 (blue line and diamonds), looking time was elevated across trials but habituation occurred at the same rate. When the stimulus strength was decreased to 15, looking time was reduced across trials and the model did not exhibit any habituation (green line and squares). The stronger stimulus strength increased the rate at which a stable WM peak was formed (blue bars) relative to the standard young infant model memory (black bars), and the weaker stimulus strength slowed the rate at which a stable WM peak was formed (green bars). For simplicity, error bars are not shown. SD (in s) for strength 15 during the first block of three trials was 4.34, 3.69, and 3.06; for strength 17 was 3.16, 2.75, and 2.91; for strength 19 was 2.99, 3.04, and 3.45. SD for strength 15 during the last block of three trials was 2.53, 2.55, and 2.57; for strength 17 was 3.11, 2.68, and 2.25; for strength 19 was 5.13, 4.69, and 5.11.

spread distribution of WM peak formation (green bars in B). These results are consistent with Hunter and Ames's (1988) multifactor model, which posits that the time course of memory formation is affected by the stimulus context.

7.2. Inter-stimulus interval

When the ISI is long, infants exhibit little or no habituation (Lewis, 1969). Long ISIs can also negatively affect infants' ability to maintain a working memory representation of a stimulus (Oakes & Ribar, 2005; Ross-Sheehy et al., 2003; Smith, Thelen, Titzer, & McLin, 1999). Schöner and Thelen (2006) showed that long ISIs slowed habituation.

In our model, long ISIs attenuate habituation because the formation of a stable WM peak is slowed or prevented. This has two sources. First, activation in H_{WM} decays over long delays, which provides little support for WM as the model repeatedly encounters a stimulus across trials. Second, WM peaks can be destabilized during long delays in the presence of noise. Fig. 13A shows the looking time of the standard model with ISIs at 5 s (black), 30 s (green), 60 s (blue), and 120 s (red). Habituation was slowed with an ISI of 30 s, slowed even more with an ISI of 60 s, and the model did not exhibit any habituation with an ISI of 120 s. The differences in habituation rate mirror the rate at which the model formed a stable WM peak across the different ISIs (see Fig. 13B). At the longest ISI, the model rarely formed a stable WM peak. These results are, once again, consistent with both Schöner and Thelen's (2006) model and Hunter and Ames's (1988)

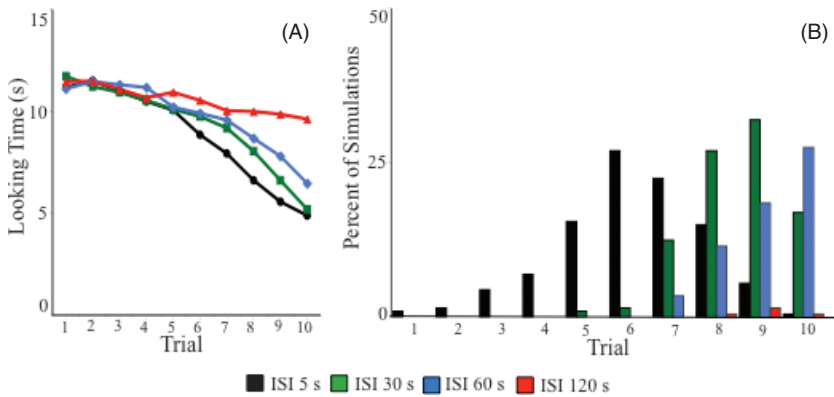


Fig. 13. The looking time (A) and distribution of trials on which a stable WM peak was formed (B) for the standard young infant model for four different ISI lengths. As the ISI was increased from the standard 5 s (black line and circles) to 30 (green line and squares) and 60 (blue line and diamonds), the model exhibited relatively little habituation. When the ISI was increased to 120 s (red line and triangles), the model exhibited no habituation. As the ISI was increased, the model acquired a stable WM peak increasingly later in the habituation phase. The model was rarely able to form a working memory when ISIs were set to 60 s (blue bars) and 120 s (red bars). For simplicity, error bars are not shown. SD (in s) for ISI 5 s during the first block of three trials was 3.16, 2.75, and 2.91; for ISI 30 s was 3.28, 2.85, and 2.80; for ISI 60 s was 3.08, 2.92, and 2.78; for ISI 120 s was 3.34, 2.84, and 2.76. SD for ISI 5 s during the last block of three trials was 3.11, 2.68, and 2.25; for ISI 30 s was 2.59, 2.88, and 2.47; for ISI 60 s was 2.41, 2.73, and 2.96; for ISI 120 s was 2.24, 2.14, and 2.44.

multifactor model which posit that task factors such as the ISI affect the time course of memory formation.

7.3. *Capturing familiarity and novelty over development*

Familiarity preferences have long been observed, but the mechanism that underlies such preferences is still poorly understood. Familiarity preferences are more pronounced early in learning and early in development (for a review, see Rose, Feldman, & Jankowski, 2004, 2007). Familiarity preferences are typically studied in the visual paired comparison procedure, in which infants' preference to look at a familiar stimulus over a novel one is assumed to reflect active encoding and initial memory formation. Why infants would be biased to look at a familiar stimulus over a novel one in single presentation tasks, however, is not immediately obvious. Indeed, it is rather striking that infants will sometimes exhibit relatively less looking to a novel stimulus on one trial relative to a familiar item on a previous trial. Schöner and Thelen (2006) were able to capture familiarity preferences in a single presentation task. Here, we probe whether our model can also capture familiarity preferences in a single presentation task as well as capture a familiarity-to-novelty shift over development. In doing so, we provide an explanation for why familiarity preferences are more prevalent early in development.

To investigate these issues, we asked whether the DNF model could quantitatively capture the only existing empirical data set examining a familiarity-to-novelty shift over development in a single presentation habituation task (Wetherford & Cohen, 1973). This study was particularly intriguing because it examined habituation in very young infants—between 6 and 12 weeks—who have not been the focus of previous formal theories of infant habituation. Results showed a dramatic developmental transition from a lack of habituation and familiarity preferences to rapid habituation and novelty preferences across a 2-week period. This developmental period is also important because there are significant changes in the control of fixation. For example, during this period, there is increased control over continuous visual tracking, orienting, and disengaging (for a review, see Johnson, 2002), and it is during this period that movements of the body and shifts of gaze become tightly coupled (Robertson et al., 2001b).

Wetherford and Cohen (1973) habituated 6-, 8-, 10-, and 12-week-olds to a two-dimensional stimulus that consisted of one shape and one color across 17 trials. On trials 2, 9, and 16, they measured infants' stimulus preferences using a different novel stimulus for each of the three trials. An example of the experimental design is shown in Fig. 14A. Infants' looking time across blocks of two trials is shown in 14B. Blocks consisted of the average looking time on adjacent trials, excluding the novel stimulus (e.g., trials 1 and 3, 4 and 5, and so on). Six- and 8-week-olds did not exhibit any evidence of habituation, 10-week-olds showed habituation late in the habituation phase, and 12-week-olds rapidly habituated. Infants' preference scores are shown in Fig. 14C. Six- and 8-week-olds showed a familiarity preference on the second and third tests, while 10-week-olds showed a novelty preference on the third test. The 12-week-olds also showed a novelty preference after the first block of trials. Thus,

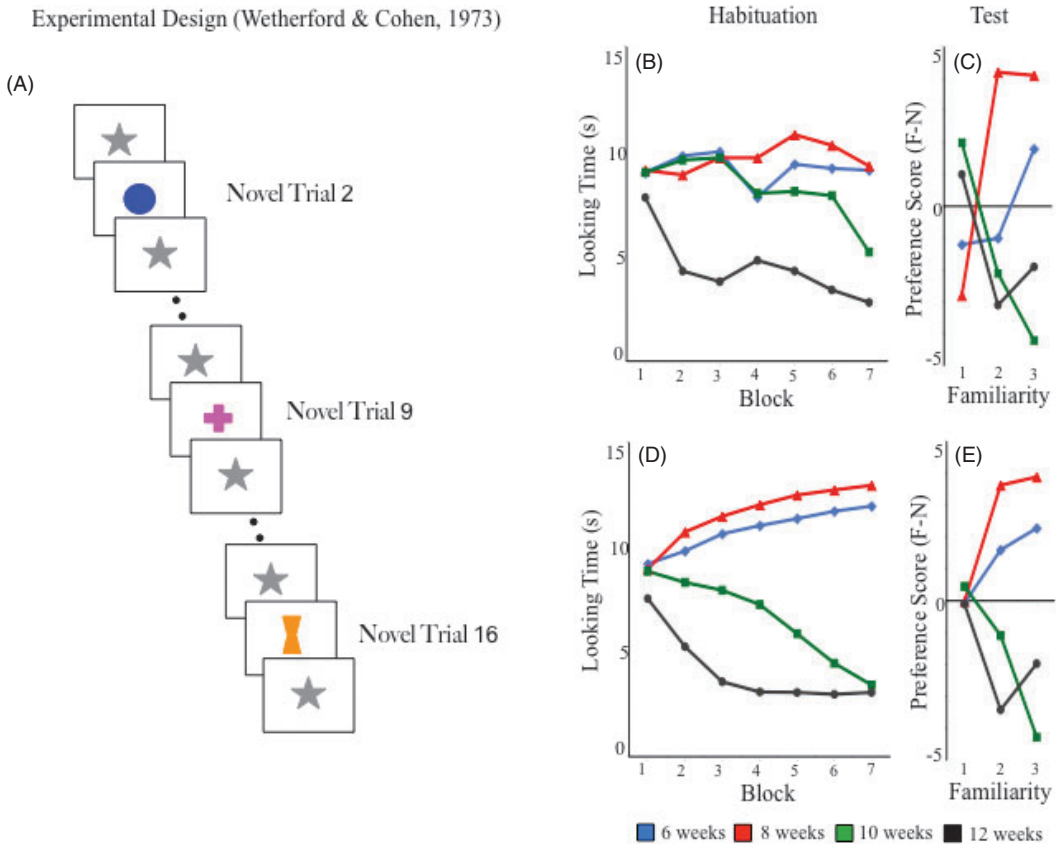


Fig. 14. (A) Experimental design from Wetherford and Cohen (1973). Six-, 8-, 10-, and 12-week-old infants were habituated to a single stimulus (shown as gray star) across seventeen 15-s trials with ISIs of 8 s. On trials 2, 9, and 16, a different novel stimulus was presented. A preference to look at the novel stimulus was calculated by subtracting looking time to the novel stimulus from looking time on the preceding trial with the familiar, habituation stimulus. (B–E) The (estimated) empirical and model results of Wetherford and Cohen (1973). (B) Looking time across seven blocks of two trials from 6-, 8-, 10-, and 12-week-old infants. Six- (blue lines and diamonds) and 8-week-old (red lines and triangles) infants exhibited no evidence of habituation. At 10 weeks of age (green lines and squares), infants exhibited a decline in looking late in habituation, and at 12 weeks of age (black lines and circles), infants rapidly habituated. (C) Infants’ change in looking to the novel stimuli on trials 2, 9, and 16 relative to the preceding trial. Six-week-old showed a trend toward a familiarity preference on the third novel test, and 8-week-olds tended to exhibit a familiarity preference on the second and third novel tests. Ten- and 12-week-olds tended to exhibit a novelty preference on the second and third novel tests. The model effectively produced the same looking behavior across trials (D) and preferences at test (E). For simplicity, error bars are not shown. SD (in s) during block 1 for 6-week model was 1.16; 8-week model was 2.48; 10-week model was 1.76; 12-week model was 1.38. SD during block 7 for 6-week model was 1.21; for 8-week model was 1.35; for 10-week model was 0.99; for 12-week model was 0.50. SD on preference scores for 6-week model on test 1 was 3.16, test 2 was 2.57, and test 3 was 2.72; SD on preference scores for 8-week model on test 1 was 4.40, test 2 was 4.44, and test 3 was 3.89; SD on preference scores for 10-week model on test 1 was 3.52, test 2 was 2.94, and test 3 was 3.60; SD on preference scores for 12-week model on test 1 was 2.94, test 2 was 3.40, and test 3 was 2.99.

across only a 2-week period, there was a developmental transition from familiarity-to-novelty preferences late in learning.

To examine whether the DNF model could capture this rapid developmental transition, we tested the model with Wetherford and Cohen's procedure. The metric similarity of the stimuli used by Wetherford and Cohen is unknown. Thus, we assumed a moderate amount of similarity among items by setting the metric distance between items to 30 neurons, half the distance between the close and far test items from the habituation stimulus in the simulations described previously. The first novel test was 60 neurons from the familiar stimulus, and the second and third novel tests were positioned 30 neurons on either side of the familiar stimulus.

We created 6-, 8-, 10-, and 12-week-old infant models by implementing the SPH (see Table 2). Pilot simulations revealed that changes to only the SPH parameters, in isolation, were not sufficient to capture the looking behavior of 6- and 8-week-olds. Given the dramatic changes in the control of fixation during this period, we added a second type of developmental change—we made the fixation dynamics less stable early in development by implementing the SPH on the fixation system. Specifically, we weakened the excitatory connection to PF from the fixation system (c_{ui}) and from PF to the fixation system (c_{iu}), as well as the self-excitation of the fixation system (c_{ii}). These changes slowed the transitions from the looking away state to the looking state and the tendency of the fixation system to reenter the looking away state once fixated. Finally, we increased the noise in PF, which affects the model's ability to form a working memory for a stimulus. Noise in PF was set to .4 for the 6-week-old model, decreased to .2 for the 8-week-old model, and returned to its base value of .12 for the 10- and 12-week-old models.

As can be seen in Fig. 14D and 14E, the model produced the same pattern of looking as infants. Simulations of 6- and 8-week-olds did not exhibit habituation, 10-week-old simulations exhibited a decline in looking during the last blocks of the habituation phase, and 12-week-old simulations exhibited a rapid decrease in looking, showing minimal looking by block 4. The novelty preferences for each age group on the three novel tests are shown in 14E. The 6-week-old model exhibited a slow increase in the strength of its familiarity preference across trials. The 8-week-old model, in contrast, exhibited a rapid increase from a null preference on the first novel test to a strong familiarity preference on the second and third novel test. Both the 10- and 12-week-old models exhibited a novelty preference on the second novel test, but only the 10-week-old model exhibited a stronger novelty preference on the third novel test.

To illustrate the dynamics that underlie this rapid developmental transition, Fig. 15 shows the state of PF and WM at the onset of the three novel tests for the 8-week-old (A-C) and 10-week-old (D-F) models. Eight-week-olds exhibit an *increasing* familiarity preference across trials. How might such a behavior arise? When the 8-week-old infant model encounters the first novel test on trial 2, H_{PF} has accumulated little activity (A; gray line, right y-axis). The model has yet to accumulate any bias to look at the familiar stimulus on previous trials and, therefore, cannot exhibit a decline in looking to what amounts to an equally novel stimulus. Across trials, activity in H_{PF} accumulates, leading to an increase in looking to the familiar stimulus. In contrast, when the model encounters the novel stimulus

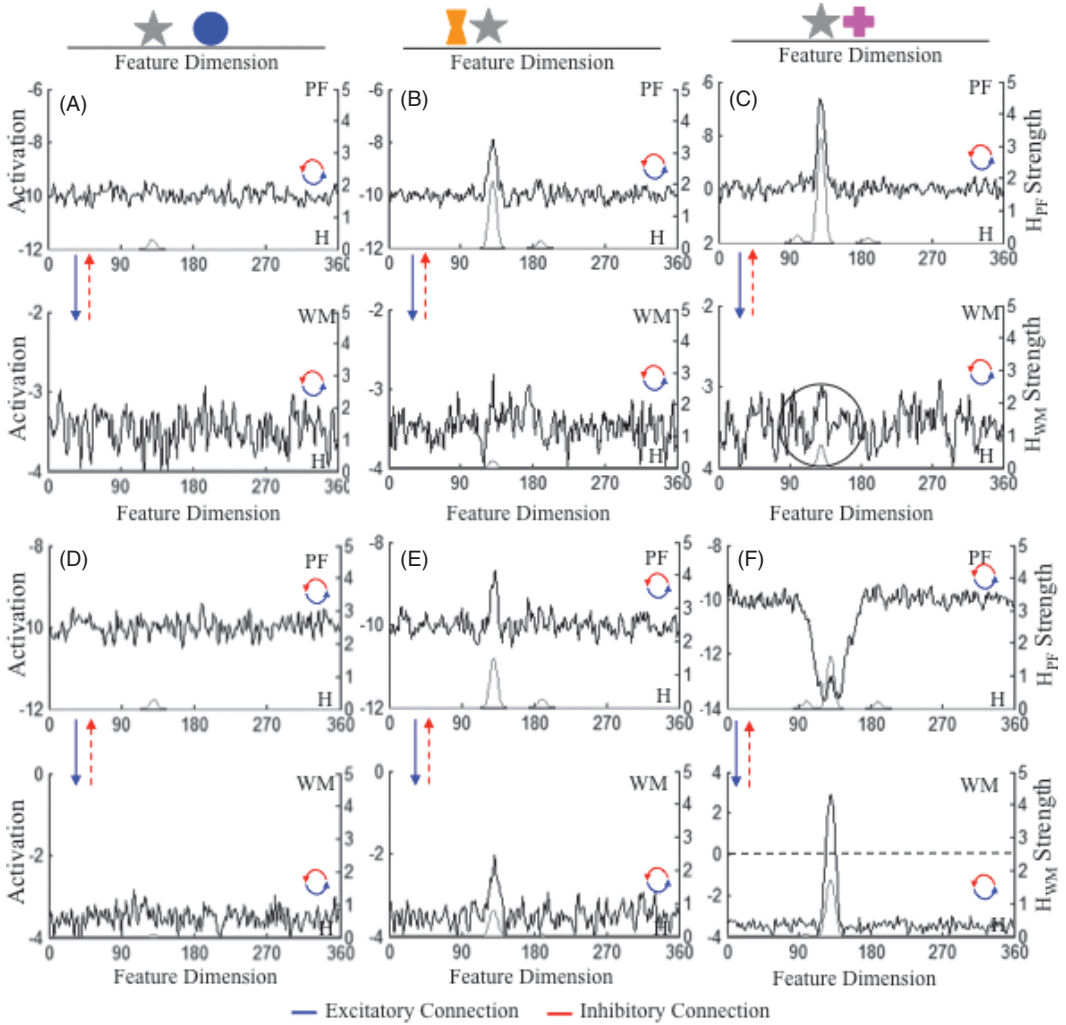


Fig. 15. The mechanisms by which looking fails to habituate at 8 weeks of age (A–C) and habituates at 10 weeks of age (D–F). The state of PF and WM is shown at the onset of the first novel test (A and D), second novel test (B and E), and third novel test (C and F). The placement of the familiar stimulus and three novel tests along a metrically organized feature dimension is shown at the top. The 8-week-old infant model acquires strong activation in H_{PF} across trials (see gray line, right y-axis in B and C), which biases looking to the familiar over the novel stimulus. The 10-week-old infant model establishes a stable WM peak late in habituation (F), which leads to a decline in looking and an increase in looking to the novel stimulus.

on trials Fig. 9B and Fig. 16C, the lack of H_{PF} activity associated with these novel feature values leads to little looking. At 8 weeks of age, then, familiarity preferences are driven by the neural dynamics associated with perceptual encoding. Note that neural interactions are too weak to support stable WM peak formation (see circle in C); consequently, no habituation occurs.

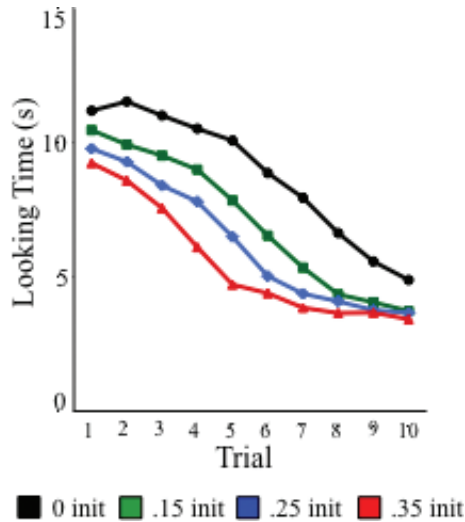


Fig. 16. Looking time of the standard young infant model as it was initialized with an increasing strength of H_{PF} and H_{WM} from 0% to 35% of that accumulated in the simulations shown in Fig. 7. As initialization strength increased, the model habituated more quickly. This mimics robust long-term memory after only short delays between first and second exposures to the habituation stimulus.

The picture is very different just 2 weeks later. Although the 10-week-old model is comparable to the 8-week-old model on the first novel test (trial 2, see D), some simulations have started to form a WM peak by the second novel test on trial Fig. 9E. This leads to a small decline in looking across simulations. By the third novel test on trial Fig. 16F, the model has established a stable WM peak, inhibition in PF is strong, and looking has declined. Consequently, the model exhibits a strong relative increase in looking to the novel stimulus.

These simulations show that small, quantitative increases in the strength of neural interactions lead to a qualitative shift in memory formation over development (for discussion of related issues, see Spencer & Perone, 2008). Interestingly, this developmental shift mirrors the qualitative transition from encoding to working memory formation that occurs over learning in the young and old infant models (see Fig. 8G and 8H). These simulations also demonstrate that the DNF model can quantitatively capture the details of infants' performance within a specific task context. It is noteworthy that the model was able to capture this data set in particular. To our knowledge, these are the first quantitative simulations of looking data from infants this young. It is also noteworthy that quantitative fits required implementing changes to the fixation system (and increasing noise). This provides a point of convergence between our modeling efforts and empirical work showing dramatic changes in fixation dynamics during this early period.

7.4. Integration of learning with real-time process

Learning in Schöner and Thelen's (2006) model did not involve excitatory memory. Our model, in contrast, learns via an excitatory Hebbian process that builds a long-term learning

history as the model looks and looks away in real time. Several studies on delayed recognition have shown that infants' long-term memory for a stimulus contributes to their subsequent looking. For example, Martin (1975) found that infants habituated to a stimulus more quickly during a second experimental session after habituating to the same stimulus during the first experimental session (for related results, see Fagan, 1973; for a review, see Rose et al., 2007). Similarly, Bahrick and Pickens (1995) found that infants spent more time looking to a familiar stimulus as the delay between initial exposure and test increased. Here, we test whether learning from one session in the DNF model produces these behavioral patterns when that learning is carried forward to a subsequent session.

To probe this, we initialized the standard, young infant model with the H_{PF} and H_{WM} accumulated from the simulations described previously (Fig. 7). To account for the decay and interference processes that occur over varying time delays, we modulated the strength of H_{PF} and H_{WM} from 0% to 35%. Fig. 16 shows the looking time across trials as the strength of H_{PF} and H_{WM} was increased from 0% to 35%. The model, like infants, habituated more quickly when it has a learning history with the stimulus (Martin, 1975). Importantly, no learning history with the stimulus (i.e., initialization 0, black line) or a weak history (i.e., initialization .15, green line) induced more looking early than did a relatively strong history (i.e., initializations .25 and .35, blue and red lines; Bahrick & Pickens, 1995). These simulations show that very little retention (<35%) is needed to have a large impact on subsequent behavior. Our Hebbian learning mechanism accounts for fast and flexible task-specific learning well, and it also accounts for the time-dependent decline that a long-term learning history has on infants' behavior. It is important to point out, however, that it is unclear whether our Hebbian learning mechanism in its current form can be applied to time delays on the order of weeks, months, or years between initial learning and subsequent testing. We are currently probing this issue in our laboratory.

8. Are learning and development the same thing?

In the DNF model, real-time cognition and behavior create cognition and behavior over the timescale of learning in the task. A provocative question is whether the real-time scale can also create behavioral changes comparable to those captured by the SPH. To test this possibility, we compared the delayed recognition simulations with a new set of developmental data produced by a fine-grained version of the SPH. In particular, we created variations of the young and old parameter sets used previously (Fig. 7), effectively breaking development up into smaller, incremental steps. To determine the specific parameters at each developmental step, we performed a linear interpolation between the young and old infant models for each parameter of the SPH (c_{uu} , c_{ww} , c_{uw} , c_{vw}). We then divided the difference between the young and old infant model parameters into proportional steps and sampled from the following proportions: $-.15$, 0 , $+.15$, $+.3$, $+.45$, where zero is the young infant or old infant model shown previously. This created 10

developmental steps, ranging from less mature (weaker) interactions to more mature (stronger) interactions.

The top row of Fig. 17 shows results from the delayed recognition simulations. In particular, these panels show the mean and standard deviation for total looking time (A), look duration (B), and the emergence of a stable WM peak (C) as the strength of the initial state of H_{PF} and H_{WM} increased from 0% to 35%. As can be seen, total looking time, look duration, and the trial on which a stable WM peak emerged decreased as the strength of the initial state of H_{PF} and H_{WM} increased from 0% to 35%.

The bottom row of Fig. 17 shows the mean total looking time (E), look duration (F), and trial of stable WM peak formation (G) for the 10 developmental models (bars represent 1 SD across the individual simulations in each set). Over development, total looking time

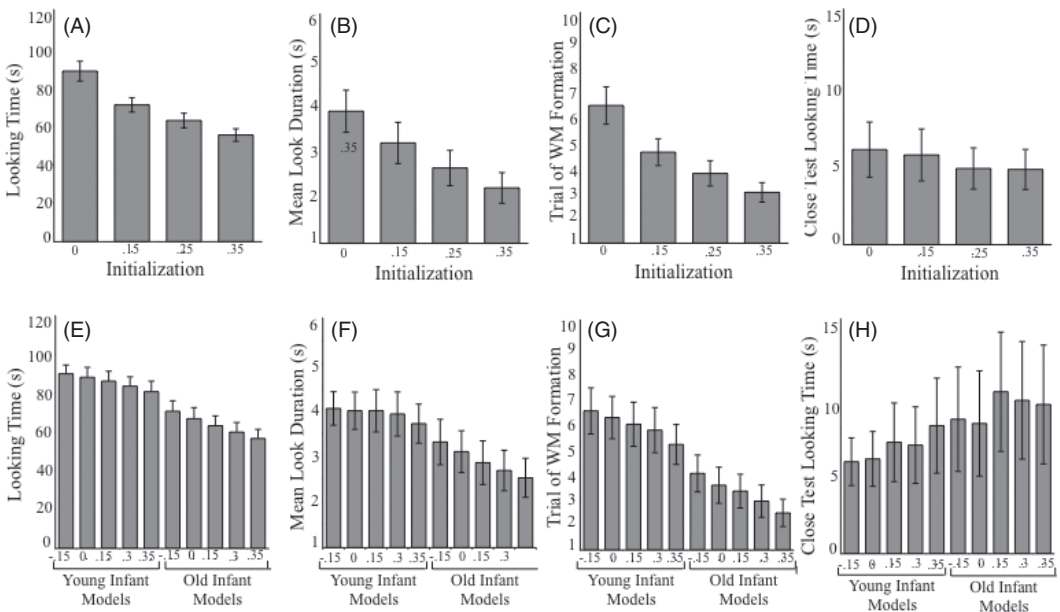


Fig. 17. The top row (A–D) illustrates how a long-term history with a stimulus affects looking behavior and working memory formation when encountering the stimulus in a habituation task. The figure shows the mean (error bars are 1 SD) looking time (A), look duration (B), and trial on which a stable WM peak emerged across trials (C) when the model was initialized with an increasing strength of H_{PF} and H_{WM} ranging from 0% to 35% of that accumulated in the simulations shown in Fig. 7. As the strength of initialization increased, looking time, mean look duration, and the trial on which a stable WM peak was formed decreased, but looking time to the close test did not change (D). The bottom row (E–H) illustrates how the strength of neural interactions affects looking behavior and working memory formation for a set of young infant and old infant model parameters. The figure shows the mean (error bars are 1 SD) looking time (E), look duration (F), and the trial on which a stable WM peak emerged across trials (G) for the young infant models and old infant models. As the strength of neural interactions increased, looking time, mean look duration, and the trial on which a stable WM peak emerged across trials decreased. Looking to the close test increased as the strength of neural interactions increased (H). Note that within the young infant and old infant groups, the relative relationship between the weakest neural interactions and the strongest interactions is preserved.

decreased, look duration decreased, and the trial on which a stable WM peak emerged decreased. Critically, these changes look remarkably like the changes produced in the delayed recognition simulations. Thus, for these three indices of performance, learning and development are nearly identical. Put differently, an increase in processing speed can arise from both mechanisms.

Interestingly, this is not the case for discrimination. Fig. 17D shows the performance of the delayed recognition model when it is shown the close test. As is clear from the figure, the model generalizes its looking to this similar novel stimulus. This is similar to the performance of the young infant model shown in H. Critically, however, as we changed the strength of neural interactions, the model started to look longer at the close test—it began to show enhanced discrimination. This indicates that our learning mechanism (Hebbian learning) does not yield enhanced discrimination, while our mechanism for development (SPH) does. We return to this topic in the General Discussion.

9. Looking matters for learning

The focus of existing theories of infant visual cognition has been on how changes in cognitive processing create changes in looking over time (e.g., Cohen, 1972b; Colombo & Mitchell, 1990; Hunter & Ames, 1988; Rose et al., 2007; Sirois & Mareschal, 2004). Theoretical accounts of the influence of looking (as an exploratory act) on learning are nonexistent. Simulations in the previous sections show that looking and learning are interdependent. However, we have yet to illustrate a central thesis of this paper—that the dynamics of looking itself directly impact learning. Here, we experimentally manipulate looking to illustrate the direct influence of looking on learning. These manipulations were inspired by work showing that manipulations of individual infants' look durations can have a profound effect on learning in the laboratory (e.g., Jankowski et al., 2001) and social settings (e.g., Landry & Chapieskie, 1988).

The promise of a model that implements looking as an active behavior is that it might explain and predict how specific manipulations of looking over time will impact subsequent learning. To examine this, we created two looking contexts, a *look bias* context and an *away bias* context. These contexts were implemented with an algorithm that added an input boost to the fixation system contingent on how the standard young infant model autonomously distributed its looks through time. In the look bias context, an extra input was provided to the fixation system when the model looked away from the stimulus for 1 s. When this occurred, a small boost (+.5) was added to c_{static} for 2 s. In the away bias context, the opposite occurred. Specifically, when the model had accumulated 2 continuous seconds of looking at the stimulus, a small boost (−.5) was subtracted from c_{static} for 1 s. Conceptually, these boosts are like “attention getters” (e.g., tapping an object) that influence shifts of gaze toward or away from locations in the task space (see Kopecz & Schöner, 1995). With the exception of the added inputs, the look bias and away bias models were identical.

The models were situated in a successive presentation habituation task. The learning phase consisted of twenty-eight 20-s trials, and the test phase consisted of two 20-s test

trials. All ISIs were 5 s. During the learning phase, the models were presented with a different stimulus randomly sampled from a set of 99 that could be centered at any site within the range 120–220 except site 170. Note that across simulations both models were presented with the exact same random distribution of stimuli. On trial 29, the biasing inputs were turned off and the models were presented with a *within* novel test, a novel stimulus that fell within the range sampled during the learning phase centered at site 170. On trial 30, the models were presented with an *outside* novel test that fell outside the range sampled during the learning phase, centered at site 270.

The looking behavior of the look bias and away bias models is shown in Fig. 18. During the learning phase, the look bias model exhibited high levels of looking (A) with a decline in looking across trials. As looking time declined, there was an associated decline in look durations (C) and an increase in the number of looks (B). The away bias model, in contrast, exhibited relatively low levels of looking (A), a moderate number of looks (B), and moderate look durations (C). Note that all three indices of looking behavior remained constant across trials. The increased looking time for the look bias model relative to the away bias

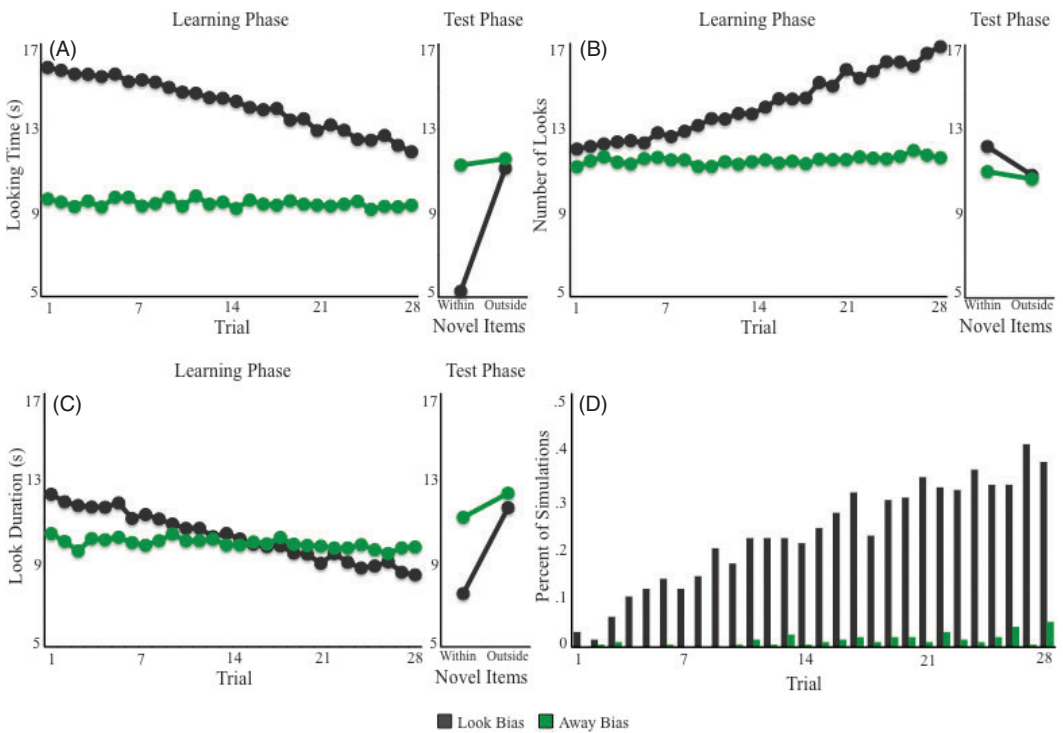


Fig. 18. The looking behavior and working memory formation of the look bias (black) and away bias (green) models. The look bias model exhibited more looking time across the learning phase than the away bias model (A). The look bias model recognized the within stimulus and renewed looking to the outside stimulus, whereas the away bias renewed looking to the within and outside test items. Across the learning phase, the look bias model exhibited an increase in looks (B) and decrease in look duration (C). The look bias model more frequently formed a stable WM peak than the away bias model (E).

model simply shows that our experimental manipulation had the expected impact. But why did one model show a change over learning while the other did not?

The two models exhibit entirely different patterns over learning because they showed different propensities to form working memories for novel stimuli. Fig. 18D shows the percent of simulations that formed a stable WM peak on a given trial. As the figure shows, the likelihood of forming a stable WM peak increased across trials for the look bias model, but remained low for the away bias model. As the look bias model began to form a stable WM peak for different, successively presented items during the learning phase, learning of previously presented items facilitated WM formation. The model, in turn, generalized looking to those items. Moreover, when the fixation system looked away, it was contingently biased to reacquire the looking state. This further enhanced the model's ability to learn about each novel stimulus. In contrast, the away bias model was contingently biased to look away from each stimulus early in the learning phase. This prevented long-term learning, which, in turn, led to little support for stable WM peak formation over time.

In addition to showing different behaviors over learning, these two model sets showed differences in looking during the test phase when the biasing inputs were turned off. As is evident in 18A, the look bias model exhibited low levels of looking to the within novel test, recognizing the stimulus as familiar. In contrast, this model showed relatively high levels of looking to the outside novel test, detecting the stimulus as novel. The away bias model looked equally to the within and outside test stimuli, encoding both novel tests as new. Note that looking on the test trials must be interpreted in the context of the general shift in baseline looking for each model that occurred when we turned the biasing inputs off. In particular, the look bias simulations showed less overall looking when the look bias input was removed, while the away bias simulations showed more overall looking when the away bias input was removed.

These simulations illustrate that how looking is distributed through time impacts learning in the moment, which impacts the long-term learning history acquired via looking. These simulations provide a particularly salient example of how looking and learning are linked—the same models with the same parameters showed dramatically different learning trajectories depending on the presence of a contingent, biasing input. We discuss the implications of these simulations in the General Discussion.

10. General discussion

Seminal theories of early cognitive and behavioral development described infants as active agents who acquire knowledge by autonomously exploring the world (Gibson, 1988; Piaget, 1952). The major challenge for these theories, however, has been to describe the link between real-time cognitive and behavioral dynamics with enough specificity to understand how cognition and behavior work together. Over the past decade, DFT has focused on this link. In this article, we proposed a DFT of visual exploration in which looking is one component of a dynamic, exploratory system that is influenced by content in the world and recent activity in the cognitive system. We formally

implemented these ideas in a DNF model that learns autonomously as it looks and looks away from a stimulus over time. We situated our model in a habituation task and showed that it effectively captured developmental change in visual habituation. Our model exhibited a rich interplay between looking and learning even in the simplest of task contexts. Below, we discuss key insights from our theory.

10.1. Insights from the DFT of infant habituation

The DNF model was able to overcome three limitations shared by existing theories, and in doing so, led to novel insights about the process of learning in a looking context. First, existing theories have not provided an account of the interdependency between looking and learning observed in experimental (Jankowski et al., 2001) and social (Landry & Chapieskie, 1988) settings. This interdependency became transparent when we anchored looking to the trial on which the model formed a stable WM peak. This anchoring revealed a rich interplay between looking and learning: Simulations that spontaneously exhibited high levels of looking early in learning established a stable WM peak for the stimulus more quickly, whereas simulations that spontaneously exhibited low levels of looking early established a stable WM peak for the stimulus more slowly.

Second, existing theories have not accounted for the nonlinear tie between looking and memory formation. In the DNF model, the formation of a stable WM peak reflects a nonlinear neural transition over learning in which the WM layer moves from the self-stabilized (input driven) to the self-sustaining (maintenance) state. This change in state led to a dramatic decline in looking time, decline in look duration, and increase in number of looks.

Third, existing theories have not tested whether developmental changes in processing speed and discrimination can arise from a common mechanistic source. This is an important limitation because (1) these changes occur during the same developmental period and (2) discrimination is one measure of processing speed. We presented a new hypothesis about the mechanisms underlying developmental change in processing speed and discrimination. In particular, we extended the SPH from studies in the domain of spatial cognition (Schutte & Spencer, 2009; Schutte et al., 2003; Simmering et al., 2008). This hypothesis posits that the strength of excitatory and inhibitory interactions increases over development. Strong neural interactions produced an increase in processing speed *and* led to enhanced discrimination. The DNF model, then, posits that developmental changes in processing speed and discrimination have a common mechanistic source.

We captured developmental differences in looking and discrimination performance by implementing the SPH by hand. This hypothesis states that neural interactions increase in strength in an experience-general manner, that is, as children accumulate diverse experiences across time and situations. But what process might lead to the specific changes we captured here? One possibility is that neural interaction strengths increase over development via the self-organizing properties of neural systems (Miikkulainen, Bednar, & Sirosh, 2005). For instance, within and cross-layer neural interaction, strength can be modulated in an activity-dependent, Hebbian manner, such that excitatory connections between coactive neurons become stronger through repeated activity. The simulation results in Fig. 17 in

which we sampled developmental change across a series of fine-grained steps suggest that an activity-dependent mechanism that produces gradual, quantitative changes in neural connections could yield systematic changes in looking and learning over development. We are currently exploring this possibility in several projects.

Interestingly, changes in behavior produced by the SPH were not isomorphic with changes produced by the contribution of a long-term learning history across multiple sessions. Both types of changes produced an increase in processing speed, but only the SPH led to enhanced discrimination over development. This contrast is striking given that both types of changes are likely to arise via activity-dependent, Hebbian processes. However, Hebbian learning in each case has a distinctive flavor. Changes in interaction strength have a more global influence on the stability of peaks in a neural field, while long-term learning influences are more local. Thus, these two mechanisms map onto what we might call task-general versus task-specific learning. Ongoing work in our lab is exploring whether a richer set of autonomous experience might enable long-term learning to mimic more properties of the SPH.

This discussion is also linked to another central topic in developmental science: What is the source of individual differences in cognition? Individual differences in looking are often attributed to developmental differences in processing speed (Colombo & Mitchell, 1990; Rose et al., 2007). Although this view has led to a rich empirical literature, the processing speed hypothesis provides only a limited view of individual differences—short lookers are fast processors and long lookers are slow processors. In the DNF model, there are three sources of individual differences. One source is stochastic forces. The fixation, perceptual, and working memory systems in the model are noisy, which influence how an individual learns over the course of a task. This leads to a second source of individual differences—each individual's long-term learning history is created emergently over the course of a task and can be carried forward in time and influence behavior. A final source of individual differences in the DNF model is the neurodevelopmental state of the infant captured by the SPH. The tendency of the DNF model to encode and remember information at a given rate is strongly influenced by neural interaction strength. We illustrated this in Fig. 17 by simulating a range of fine-grained developmental steps, but these simulations could also be placed in the context of individual differences. In particular, each parameter set could be viewed as a different individual within some range of a normative developmental parameter set (see Gilmore & Thomas, 2002 for a similar approach). We believe that this last source of individual differences most closely resembles the processing speed hypothesis. However, if changes in neural interaction strength can emerge in an activity-dependent way as we suggested above, it is possible that the stochastic contribution to learning over the task time scale combined with a long-term learning history accumulated across multiple tasks would be sufficient to mimic the behaviors associated with changes in neurodevelopmental state we observed here.

10.2. *Comparison with other theories*

Our theory closely resembles seminal conceptual theories of infant habituation. For example, our model resembles Cohen's (1972b) dual-process model. The dual-process

model situated an active infant in a task space who looks and looks away from a stimulus over time. The model posited that when the infant looks, looking is sustained by encoding of the perceptual features. As the stimulus is repeatedly presented, long-term memory formation supports recognition, leading infants to look away. Similarly, our model situates an active, autonomous agent in a task space that looks at and encodes a stimulus. Encoding contributes to the maintenance of looking and memory formation, and memory formation contributes to the release of fixation.

Our theory shares many concepts with existing neural network models as well. Most models of infant habituation implement some comparator process (e.g., French et al., 2004). Looking in these models declines as the stimulus representation begins to match or can assimilate the input. In this regard, our model is similar. In addition, in some models of infant habituation, a stimulus is processed, remembered, and looking declines through a combination of excitatory and inhibitory processes (Sirois & Mareschal, 2004). In this regard, our model is also similar.

However, our model departs in three important ways from existing models. First, our model is an autonomous exploratory system that evolves over multiple time scales—looking evolves on the second-to-second time scale in the same spirit as Robertson et al. (2004) and is integrated with the trial-to-trial dynamics of memory formation. Second, looking time is not only influenced by memory formation but also the dynamics of fixation, events in the world, and the state of encoding. This enables the DNF model, like infants, to respond more robustly to stimuli that demand processing resources or to manipulations of the physical world by others. Last, habituation in our model arises through the interaction of general cognitive processes that have accounted for visual recognition processes and change detection at later points in development (Johnson et al., 2009). This opens the door to studying developmental continuity in these basic visual cognitive processes. Other models implement neurally plausible forms of representation formation, but it is not always clear how these models relate to basic perceptual and cognitive processes more generally.

Our theory of infant habituation also shares many qualities with the theory proposed by Schöner and Thelen (2006). Perhaps most notably, both models specify the mechanisms that underlie familiarity preferences in successive presentation habituation tasks and exploited these mechanisms to quantitatively capture an empirical data set. We illustrated this by quantitatively capturing an empirical data set from Wetherford and Cohen (1973) showing a rapid familiarity-to-novelty shift over development. However, our model departs from Schöner and Thelen (2006) in several ways. In their model, habituation happened via an inhibitory long-term memory. Habituation in our model happens as a working memory is formed and strong excitatory long-term memory accumulates. This enables our model to create an excitatory learning history in real time and carry that history forward to new learning contexts. In addition, developmental change in looking and learning in our model happens as the strength of excitatory and inhibitory interactions increases. Schöner and Thelen probed developmental change simply by adjusting the initial state of the excitatory layer that contributes to the rate at which inhibition accumulates and looking declines. As discussed above, our theory has a richer source of change over the longer time scales of learning. We

suspect these multiple sources will be critical to understanding both the origin of individual differences and the origin of developmental change.

10.3. Limitations and future directions

10.3.1. Beyond habituation

The single presentation habituation task is commonly used to probe infants' developing perceptual and cognitive abilities. It is also the simplest context within which to probe the interplay between looking and learning. However, one emerging question in the infant cognition literature is how looking and learning differ across task contexts in which infants look at a single item at one location or pairs of items at different locations (see Oakes, Horst, Kovack-Lesh, & Perone, 2008). Infants perform differently in these two contexts (Oakes & Ribar, 2005; see also Kovack-Lesh & Oakes, 2007).

The DNF model sheds light on these differences. In the single presentation task, looks away from the stimulus are looks to task-irrelevant locations. This can result in spontaneous decay of WM peaks. In paired presentation tasks, in contrast, looks away from one stimulus might be looks to another identical or similar stimulus which can facilitate continued WM formation. This, in turn, can foster more rapid learning. In addition, what constitutes evidence of recognition and discrimination differs across single and paired presentation contexts. In single presentation tasks, recognition is inferred from a decline in looking to the habituation stimulus and discrimination inferred when infants exhibit elevated levels of looking to a novel stimulus on a subsequent trial. In paired presentation contexts, in contrast, recognition is inferred from a preference to look at a novel over a familiar stimulus within a single trial.

Perone, Simmering, and Spencer (2011) have shown that the basic theoretical concepts presented here generalize to a paired presentation context. They situated a DNF model in a change-preference task designed by Ross-Sheehy et al. (2003) to estimate visual WM capacity development during infancy. Infants viewed two displays of colored squares simultaneously blinking on and off. On a no-change display, all of the items remained the same across blinks. On a change display, one item changed to a new color. A preference for the change display was interpreted as memory for the number of items per display (i.e., set size). The results showed that 6-month-olds exhibited a change preference at set size one. Ten-month-olds exhibited change preferences up to set size four.

In the Perone et al. (2011) DNF model, the fixation system looked at left, right, and away locations in a winner-take-all fashion. Fixating one location opened a perceptual gate only for the items present at that location. After exploring the displays, the model began to recognize items on the no-change display and look away. When fixating the change display, in contrast, the model encoded the novel, changing item. This led the model to prefer to look at the change display longer than the no-change display.

In addition, Perone et al. (2011) implemented the SPH in the model and, quite remarkably, showed that the very same hypothesis that has captured developmental change in children's performance in spatial working memory tasks (Schutte & Spencer,

2009) and infant habituation also captured the developmental differences between young and older infants. In this context in which the model was encoding multiple items across multiple locations, the SPH had different implications for performance. In particular, the young model formed less stable WM peaks that spontaneously decayed across fixations at which multiple, different items were located. However, the old infant model formed more stable WM peaks, enabling it to recognize items on the no-change display after looks away. The strengthening of neural interactions appears to be a general developmental mechanism that has diverse influences on neural and behavioral organization across contexts.

10.3.2. Multidimensional learning

Our simulations focused on learning and discriminating along a single, metrically organized dimension. We showed that even this simple stimulus context yields novel insights into the system under study. The DNF model can be expanded to provide an account of learning about multidimensional stimulus events by reciprocally coupling neural fields tuned to different dimensions to the fixation system. Consider a simple example. When the model looks at a green square, it would encode and form a memory along color and shape dimensions in parallel. If the model were tested with a red square (novel color), the model would recognize the familiar shape but renew encoding of the novel color. Interestingly, looking in this case would be less than if the model were tested with a red circle (novel color and shape). Thus, the number of novel dimensions at test would affect dishabituation. Importantly, the stimulus strength or experience on a specific dimension can also impact memory formation, recognition, and novelty detection for features on that dimension. Such issues have been of substantial interest in the past decade as researchers probe what infants remember about different, simultaneously present dimensions (Horst et al., 2005; Perone, Madole, Ross-Sheehy, Carey, & Oakes, 2008; Robinson & Sloutsky, 2004). We are currently exploring these possibilities in a multidimensional variant of the model presented here.

10.3.3. Autonomous exploration and learning in social contexts

In this article, we developed an autonomous exploratory system that is embodied, situated in its environment. This opens up a rich connection between the looking behavior of the model and the environment it is situated in. One implication of this is that the model can look, like infants, at a world that includes dynamic, stimulating events that influence where it looks. We demonstrated this aspect of the model by experimentally manipulating where the model looks in two contexts: a look bias context and an away bias context. These contexts not only influenced looking and learning but also how the models explored novel items. These simulations were inspired by demonstrations that experimental manipulations of looking behavior can influence learning and exploration (Jankowski et al., 2001; Landry & Chapieskie, 1988; Parrinello & Ruff, 1988).

We contend that this provides a critical link to studying how social partners influence how infants distribute their looks, learn, and develop. For example, intervention studies

that train parents to maintain their preterm infant's gaze on objects result in positive developmental change in basic social and cognitive abilities (Landry et al., 2008). Working with an embodied system that evolves over multiple time scales enables us to explore how such manipulations impact learning across real and developmental time scales.

10.4. *Neural grounding*

DNFs specify the link between cognitive and behavioral dynamics with a high degree of neural realism (for a review, see Spencer et al., 2009). This realism enables DNFs to interface with neurophysiological measures. For example, neuronal interactions within DNFs have captured the distribution of population activity in cat visual cortex in response to simple light stimulation (Jancke et al., 1999; for similar investigations see Bastian et al., 2003). In addition, DNFs have been used to predict electrophysiological measures. For example, McDowell, Jeka, Schöner, and Hatfield (2002) used concepts of DNFs to predict changes in event-related potentials (ERPs) based on the frequency of reaching responses as well as the metric similarity of the target locations. The dynamics shown here resemble ERP studies with infants. For example, Snyder (2010; see also Snyder, 2007) found that a decrease in ERP amplitude during encoding was associated with stronger preferences for novelty during test. In the DNF model, the emergence of a stable WM peak suppresses activity in PF, which, in turn, enables the DNF to exhibit differential neural and behavioral responses for familiar versus novel items. This link suggests that DNFs may provide a fertile foundation for understanding developmental change in brain-behavior relations.

11. Conclusions

Developmental scientists have long held that children create knowledge through active exploration in their environment. Looking is one of the few behaviors that young infants can systematically and reliably engage in and a key behavior by which they begin to learn about the visual world. Looking is also a powerful empirical tool, and looking is widely recognized to be a window into the developing cognitive and neural system. In this article, we recast looking as part of a dynamic exploratory system. We illustrated how looking contributes to the dynamics of memory formation, showing that the act of looking and memory are inseparable aspects of the processes we study in infant cognition. Although we focused on the simplest situation in which looking and learning are linked—single presentation habituation—the rich interplay between looking and learning even in this context highlights how important it is to understand this interplay when interpreting looking measures in infancy.

The DNF model has important implications for thinking about looking as we observe it in the laboratory. Looking over the course of a task is a slice in time of a historical system behaving and creating a history that will impact the future behavior of that sys-

tem (Oyama, 2002). Looking over the course of a task cannot be separated from the long-term learning history that an infant brings to the task, an individual's developmental state, and stochastic forces. We contend that the DNF model can foster an appreciation for this level of complexity, helping us to understand the rich array of looking behaviors infants exhibit in the lab, in naturalistic contexts, and in contexts that include social partners.

Notes

1. We use the term “capture” throughout to mean produce behavioral patterns quantitatively or qualitatively comparable to the means and standard deviations produced by infants, as well as, where relevant, across conditions and development.
2. The “+” in three-layer+ model refers to our addition of Hebbian layers to Johnson et al.'s model.

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Appendix

Much of our empirical understanding of infants' developing cognitive abilities has come from looking measures using the infant-control procedure. Historically, the procedure's popularity stems from a critical assumption: The procedure tailors the exposure time needed to learn about a stimulus to each individual's memory formation abilities (see Danemiller, 1984; Deloache, 1975, 1976). For example, some infants may form a memory for a stimulus quickly, exhibit a sharp decline in looking, and satisfy the habituation criterion after only a few trials and begin the test phase. Other infants may form a memory for a stimulus more slowly, exhibit a gradual decline in looking, and satisfy the habituation criterion after several trials. By tailoring exposure time based on these individual differences, researchers assume that infants form comparable memory representations heading into the test phase.

A number of studies cast doubt on this assumption. For example, fast and slow habituators perform differently at test (Cashon & Cohen, 2000; McCall, Hogarty, Hamilton, & Vincent, 1973; see also Schöner & Thelen, 2006). If the procedure equates for individual differences in learning, then we would expect individuals to exhibit similar performance at test. Moreover, there is no clear consensus on how procedural variants affect the state of memory entering the test phase. Do some procedures ensure that infants have a more robust memory entering the test phase than others?

The dynamic neural field (DNF) model is ideally situated to address these issues because looking in the model, as with infants, can be calculated on each trial. Thus, in the simulations that follow, we situated the DNF model in two types of infant-control procedures—the sliding-block design and the fixed-block design. The simulations provide two critical insights. First, they show how emergent individual differences in looking and learning influence the procedure and, reversely, how the procedure influences looking and learning. Second, our simulations show the state of memory entering

the test phase is more robust in the fixed-block design, particularly for fast-habituating simulations.

In the sliding-block design, looking is calculated across the first block of (typically) three consecutive trials and the criterion is met when looking on any three consecutive trials is at least 50% of looking during the first block. We implemented the sliding-block design using the standard young infant model. Each trial was terminated once the model looked away for three consecutive seconds or until 20 s had elapsed. The interstimulus interval was fixed at 5 s. Looking was calculated across overlapping blocks of three consecutive trials (e.g., block 1 is trials 1–3, block 2 is trials 2–4, and so on). There was a maximum of 12 trials. In our implementation of the sliding-block design, then, the model could meet the habituation criterion on any trial between 4 and 12.

The top portion of Appendix Table 1 shows simulation results for the sliding-block design. To illustrate how looking contributes to satisfying the habituation criterion, we parsed simulations into groups based on the trial that the model met the habituation criterion. Note that we increased our simulation batch size from 200 to 1000 to ensure that we could evaluate the behavior of a relatively large number of simulations regardless of the trial on which the criterion was met. The model most frequently met the habituation criterion on trials 7–12. As with infants, fast-habituating simulations accumulated more looking time during the first block than slow-habituating simulations. The longest look (peak look) for fast-habituating simulations was also longer and occurred earlier in habituation than for slow-habituating simulations. Interestingly, the average trial on which a stable WM peak was formed and the trial on which the habituation criterion was met became disconnected as the trials to criterion increased. In particular, simulations that met the criterion early only formed a working memory slightly earlier than simulations that satisfied the criterion later. This happens because fast-habituating simulations accumulated high levels of looking during the first block, which set a high criterion. As fast-habituating simulations formed a working memory, looking declined and the criterion was satisfied. Slow-habituating simulations, in contrast, exhibited less looking during the first block, which set a low criterion. Despite the low looking early, these simulations tended to form a stable WM peak relatively quickly. However, these simulations did not move on to test until later because they were unable to satisfy the low criterion set early in learning.

	Trials to Criterion										
	Four	Five	Six	Seven	Eight	Nine	Ten	Eleven	Twelve	None	
Sliding-block											
<i>n</i>	0	4	17	41	81	121	154	147	125	310	
Total looking				52.34 (8.24)	60.75 (8.20)	64.52 (7.86)	70.45 (8.71)	76.55 (8.59)	82.30 (8.69)	87.02 (9.59)	
Looking first block				30.47 (4.62)	30.40 (5.11)	27.86 (4.01)	27.75 (4.44)	26.76 (3.88)	26.44 (3.92)	24.65 (4.18)	
Looking last block				12.96 (2.56)	13.10 (2.93)	11.70 (2.51)	11.32 (2.62)	10.83 (2.30)	10.62 (2.32)	17.37 (3.91)	
Last trial				2.62 (1.73)	2.35 (1.58)	2.50 (1.78)	2.21 (1.42)	2.14 (1.34)	2.46 (1.52)	5.05 (2.99)	
Familiar test				6.33 (2.71)	5.19 (2.78)	5.00 (3.01)	4.80 (3.14)	3.82 (2.50)	4.02 (4.96)	3.81 (2.69)	
Close test				7.12 (3.49)	6.19 (4.36)	6.88 (4.89)	5.49 (4.28)	5.17 (4.24)	4.96 (3.73)	4.91 (4.33)	
Far test				9.97 (3.82)	9.22 (3.30)	8.92 (3.06)	9.52 (3.50)	9.22 (3.15)	9.02 (3.35)	9.19 (3.35)	
Peak look				13.10 (2.95)	13.19 (2.72)	12.49 (2.48)	12.15 (2.39)	11.97 (2.39)	11.74 (2.09)	11.77 (2.26)	
Peak look trial				1.85 (1.04)	2.47 (1.33)	2.89 (1.72)	3.12 (1.99)	3.85 (2.35)	3.78 (2.55)	5.16 (3.08)	
Trial of working memory formation				4.44 (1.45)	5.37 (1.66)	5.67 (1.77)	5.92 (1.89)	6.42 (1.79)	6.50 (2.07)	6.60 (2.04)	
Fixed-block											
<i>n</i>			27			189			369	415	
Total looking						63.59 (7.87)			80.15 (9.87)	84.94 (9.72)	
Looking first block						28.77 (4.53)			27.10 (4.24)	24.72 (3.76)	
Looking last block						11.25 (2.81)			9.46 (2.86)	17.30 (3.74)	
Last trial						2.90 (1.42)			2.86 (1.97)	5.31 (2.94)	
Familiar test						4.97 (2.91)			3.61 (2.61)	3.65 (2.64)	
Close test						6.27 (4.57)			4.66 (4.06)	4.62 (3.94)	
Far test						8.90 (3.18)			9.05 (3.16)	9.09 (3.29)	
Peak look						12.50 (2.65)			12.09 (2.36)	11.63 (2.16)	
Peak look trial						2.48 (1.51)			3.53 (2.38)	4.89 (3.15)	
Trial of working memory formation						5.34 (1.69)			6.15 (1.89)	6.44 (1.91)	

Fast and slow habituation has implications for performance at test. In the infant-control procedure, infants are typically re-presented with the habituation stimulus on the first trial postcriterion as a baseline measure of looking. Previous studies have shown that infants' looking to the postcriterion habituation stimulus is elevated relative to the last habituation trial (Cohen & Menten, 1981). Inspection of Appendix Table 1 shows that the DNF model produces this behavior. This was particularly pronounced for simulations that met the criterion early. The left portion of Appendix Fig. 1 shows the mechanisms that underlie this behavior. This figure shows the state of PF and WM entering the postcriterion trial for fast-habituating simulations that met the criterion on trial 7 (blue line) and slow-habituating simulations that met the criterion on trial 12 (black line). Fast-habituating simulations had weaker WM activity and weaker inhibition in PF than slow-habituating simulations, which supports longer looking when the habituation stimulus is re-presented.

The state of memory entering the test phase for fast-habituating simulations is very different when the model is situated in the fixed-block design. In the fixed-block design, looking is calculated across discrete, nonoverlapping blocks of trials. In our implementation of the fixed-block design, there was a maximum of four blocks of three trials (e.g., block 1 was trials 1–3, block 2 was trials 4–6, and so on) for a maximum of 12 trials. The model could meet the criterion on trials 6, 9, or 12. Each trial was terminated when the model looked away for 3 consecutive seconds or 20 s had elapsed.

The sliding-block and fixed-block designs differ in an important way. In the sliding-block design, the habituation criterion can be met on any successive trial. This means that a sudden decline of looking on one trial can have a significant impact on whether the model meets the criterion. For example, if an infant exhibits little looking on trial 4, total looking on the second block (trials 2–4) may satisfy the criterion based on the first block (trials 1–3). In the fixed-block design, the habituation criterion can only be met on nonoverlapping blocks of trials. A sudden decline in looking, therefore, typically has a less immediate impact. If an infant exhibits little looking on trial 4, for instance, total looking on the second block (trials 4–6) may be low, but it might not satisfy the criterion if looking is renewed on trial 5 or 6. This methodological difference has an important consequence—an infant can satisfy the habituation criterion more easily in the sliding-block than in the fixed-block design. This is evident in our simulations: as can be seen in Appendix Table 1, more simulations failed to satisfy the habituation criterion with the fixed block (415) than with the sliding-block design (310; see Horst et al., 2005 for similar results).

In our analysis of the sliding-block design, the state of memory entering test was weak for fast-habituating simulations. How does the fixed-block design impact the state of memory entering test for fast-habituating simulations? The right portion of Appendix Fig. 1 shows the state of PF and WM for fast-habituating simulations that met the criterion on trial 9 (blue line) and slow-habituating simulations that met the criterion on trial 12 (black line). WM activity and inhibition in PF were stronger for fast-habituating simulations in the fixed-block design than fast-habituating simulations in the sliding-block design. Importantly, trial 9 in the fixed-block design is only the second opportunity to satisfy the habituation criterion. This forces simulations that acquired a stable WM peak early and exhibited a decline in looking to be exposed to the stimulus for several more trials. Indeed, 39% of the simulations

that met the habituation criterion on trial 9 in the fixed-block design would have met the criterion prior to trial 9 in the sliding-block design. WM activity and inhibition in PF were comparable for slow-habituating simulations in both designs.

Appendix references

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Appendix Fig. 1. Left portion shows the state of PF and WM for fast-habituating (blue line) and slow-habituating (black line) simulations in the sliding-block design. Right portion shows the state of PF and WM for fast-habituating (blue line) and slow-habituating (black line) simulations in the fixed-block design. For both designs, WM activity and inhibition in PF were stronger for slow-habituating than fast-habituating simulations. WM activity and inhibition in PF were stronger for fast-habituating simulations in the fixed-block design.

