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Using dynamic neural fields to understand the development of metric representations in typically developing and at-risk infant populations

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USING DYNAMIC NEURAL FIELDS TO UNDERSTAND THE DEVELOPMENTAL COURSE OF METRIC REPRESENTATIONS IN TYPICALLY DEVELOPING AND AT-RISK INFANTS

by

Sammy Perone

An Abstract

Of a thesis submitted in partial fulfillment
of the requirements for the Doctor of
Philosophy degree in Psychology
in the Graduate College of
The University of Iowa

December 2010

Thesis Supervisor: Professor John P. Spencer

ABSTRACT

During the past half-century, the experimental use of looking measures have led to many new discoveries about the origins of cognition. Across the first year, infants' looking changes in predictable ways, they form memories more quickly, and they begin to discriminate between subtly different stimuli. However, a rich understanding of the link between looking and cognitive dynamics has yet to be achieved. This was the overarching goal of this thesis.

I developed a new Dynamic Field Theory of infant looking and memory and formally implemented this theory in a Dynamic Neural Field model. In Experiment 1, I tested and confirmed a prediction of the model with 10-month-old infants. The prediction was that robust memory can induce both a familiarity and novelty bias depending on the metric similarity of the familiar and novel items at which infants look. This prediction is a radical one because all existing theories posit that familiarity biases arise from weak memory.

One central innovation of the DNF model is that it captures developmental change in the rate at which memories are formed and discrimination within the same system and from the same developmental mechanism. With a validated theory in hand, in Experiment 2 I tested this theoretical assumption. In particular, I measured the looking dynamics and discrimination performance of 5-, 7-, and 10-month-old infants. The results showed that infants' exhibited an increased ability to discriminate between dissimilar familiar and novel items between 5 and 7 months of age. The results also showed that three well-known looking indices of memory formation also generally change between 5 and 7 months of age. Additionally, individual differences in these looking indices were predictive of infants’ discrimination performance. These findings indicate that, indeed, looking and discrimination change together, and are linked within individuals, over development.

In Experiment 3 I tested developmental change in the discrimination abilities of at-risk infants. Previous studies have shown that the looking dynamics and recognition performance of at-risk infants is delayed but, critically, follows the same developmental trajectory as typically developing infants. Consistent with these previous studies, the looking dynamics of at-risk infants did change in predictable ways over development. However, their discrimination performance did not – young at-risk infants, unlike young typically developing infants or older at-risk infants, discriminated between dissimilar familiar and novel items.

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Graduate College
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CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

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has been approved by the Examining Committee
for the thesis requirement for the Doctor of Philosophy
degree in Psychology at the December 2010 graduation.

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John P. Spencer, Thesis Supervisor

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Michael Acarregui

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A friend of mine once told me that not everyone on the street has a Ph.D. I have often lost sight of this fact, but it is true that the degree is a major professional accomplishment. Yet it is a shame that the front of this thesis has printed on it only one name. It is true, yes, that I put pen to paper, worked tirelessly morning, day, and night. And, indeed, I am proud of this thesis and believe it tells the story of what is now many years of work. It is the wonderful people that I have had the good fortune to know, however, that have made it possible for me to sit here today with thesis in hand. It is their names that should be placed upon its front.

There is no doubt that I would not be here today had I not met my wife, Jessica Perone, seventeen years ago. We have walked down many paths together. Her support is unmatched, and her stability has always helped me see the best path to walk along when I could not. My love and respect for her cannot be expressed in words. We have two beautiful girls, Lily Ann and Anita, who inspire me every day to improve on my faults. When I stumble and fall, as I often do, a look at their faces and the sounds of their voices lift me and stand me up straight again.

There is also no doubt that I would not be here today if it were not for my sister, Renee Perone, and her husband, Craig Corcoran. Nearly twenty years ago, they set aside their personal and professional aspirations so that I might pursue mine. Every breath I take could not be so fresh, so cleansing, had they not sacrificed for me. My admiration for them will never cease.

The most powerful lesson that I have learned to date was taught to me by my mother, Anita Perone. She showed me that family rises up together in times of happiness and sadness. Her passing was an event that shaped my life and the life of my sisters – Vita, Amy, and Renee. Together, we have traveled the road less traveled. This thesis is a tribute to our perseverance. This thesis is also a tribute to my father, Sam Perone, who let me wander along that road that eventually led me here. A brief discussion with him, no matter how brief, always revitalizes my spirit. With love and respect, I thank him.

My journey has been shared by many friends as well, especially long time friend Brian Diamond. Together, we have turned the sometimes mundane into the memorable. It does not go unnoticed the effort that he puts forth so that our friendship may continue. For that, I thank him. I am also indebted to Mark Hautt, who has shown me through his action that it is possible to separate life from work. I see now a different world before me when I wake each and every day than I did before.

The content of this thesis would not be so had I not had the opportunity to work with so many remarkable scholars. I have long asked why a given individual experiences the world and acts in it in the particular way that they do. Initially, I sought philosophical explanations. It was at Purdue University that Barb Younger introduced me to cognitive development, and I knew, instantly, that the scientific study of the origins of knowledge was the clearest path to answer these questions.

Lisa Oakes taught me the tools of the trade. She showed me how to study infant cognitive development using looking measures as rigorously as possible. She introduced me to a historical literature on looking and memory that prompted me to think about the link between looking and cognitive dynamics, ultimately giving birth to this thesis.

I would like to thank the members of my dissertation committee - John Spencer, Larissa Samuelson, Bob McMurray, Susan Cook, and Michael Acarregui. No member was chosen by accident. Each and every member has over my graduate career inspired me in a unique way to think deeply about the behaviors I study and respect development for the complex process that it is. Many thanks to Bob McMurray, who gave me a crash course in regression and factor analysis and answered my many, many questions on the topic. I believe these tools enhanced this thesis above and beyond what it would have been and will have a lasting impact on the research questions I seek to answer.

The staff in the Pediatric Specialty Clinic at the Children's Hospital of Iowa have also made a substantial contribution to this thesis. Katie Breitbach, Sara Gordon, and Diane Eastman worked on a day-to-day basis with me to recruit and test at-risk infants visiting the clinic. I would especially like to thank Diane, who put forth a tremendous effort gathering data for my analyses on risk factors surrounding the neonatal period. I would also like to thank Michael Acarregui, who provided me the rare opportunity to work with at-risk infants. Mike has challenged me to think about the whole context in which a child develops.

Over the course of my graduate career, I have had the opportunity to work side-by-side with numerous top-notch graduate students. They have all been irreplaceable instructors, as it is with them, seemingly with no sense of time, that many partial thoughts have developed into groundbreaking ideas. I would like to especially acknowledge Jeff Johnson and Vanessa Simmering. It was with them, step-by-step together, that we learned how to use a very complex class of models – Dynamic Neural Fields – and connected the dots between systems concepts and the details of our research.

I would also like to acknowledge Gregor Schöner. After all, it was he and his colleague Esther Thelen who initially tackled the challenging problem of linking looking and cognitive dynamics during infancy within a systems framework. I will long remember the afternoon that Gregor introduced me, a young graduate student at the time, to the bifurcation concept. The concept, mathematically, was puzzling, and so the link to my work was obscure. Amazingly, I recently taught the concepts along side of him.

This achievement is attributable to the most fortuitous event in my professional career – the crossing of my path with the path of my advisor, John Spencer. There are few words for me to describe how I think and feel about John. All of my attempts to do so have failed. I can say, at the least, that he helped me harness my intuitive systems thinking. He introduced me to a set of concepts known as Dynamic Systems Theory, and he introduced me to a formal approach that solves the some times abstract nature of those concepts – the Dynamic Field Theory.

Looking back, I sit here today with the particular thesis in hand that is because he has struck the perfect balance as an advisor to me. On the one hand, he has been an active participant in my development as a young scientist. On the other hand, he has let me freely pursue as many lines of thought as needed to arrive at a solution to the research problems I was tackling.

When I think of John, I think of someone who knows what is most important in a scientific career – the life you aspire to lead. I cannot count the number of times in which he has acted selflessly, no matter the consequence, to support me – and sometimes literally walk me through - as I pursued my aspirations. There are no thanks that I could give to John that would be thanks enough. Much of what I have learned from John, as a person, will be passed along through my actions to my future students. He might have it no other way.

ABSTRACT

During the past half-century, the experimental use of looking measures have led to many new discoveries about the origins of cognition. Across the first year, infants' looking changes in predictable ways, they form memories more quickly, and they begin to discriminate between subtly different stimuli. However, a rich understanding of the link between looking and cognitive dynamics has yet to be achieved. This was the overarching goal of this thesis.

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One central innovation of the DNF model is that it captures developmental change in the rate at which memories are formed and discrimination within the same system and from the same developmental mechanism. With a validated theory in hand, in Experiment 2 I tested this theoretical assumption. In particular, I measured the looking dynamics and discrimination performance of 5-, 7-, and 10-month-old infants. The results showed that infants' exhibited an increased ability to discriminate between dissimilar familiar and novel items between 5 and 7 months of age. The results also showed that three well-known looking indices of memory formation also generally change between 5 and 7 months of age. Additionally, individual differences in these looking indices were

predictive of infants' discrimination performance. These findings indicate that, indeed, looking and discrimination change together, and are linked within individuals, over development.

In Experiment 3 I tested developmental change in the discrimination abilities of at-risk infants. Previous studies have shown that the looking dynamics and recognition performance of at-risk infants is delayed but, critically, follows the same developmental trajectory as typically developing infants. Consistent with these previous studies, the looking dynamics of at-risk infants did change in predictable ways over development. However, their discrimination performance did not – young at-risk infants, unlike young typically developing infants or older at-risk infants, discriminated between dissimilar familiar and novel items.

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MEASURING INFANT LOOKING BEHAVIOR

Our understanding of the origins of human cognition is largely attributable to measures of infant looking. The experimental investigation of infant cognition flourished once it was discovered that infants' looking to visual stimuli in the laboratory was a reliable behavioral measure of memory formation and discrimination. In the 1960s, researchers developed innovative habituation procedures to study basic perceptual and cognitive development in infants. These procedures were based on two central observations. One observation is that infants' looking time decreases as they are repeatedly shown a single stimulus across a series of presentations (Cohen, Gelber, & Lazar, 1971). The other observation is that looking time recovers following this habituation phase if infants are shown a perceptually distinct novel stimulus.

Looking measures have led to a rich empirical database on the cognitive abilities of infants and developmental changes in basic attentional, memory, and recognition processes. For instance, habituation studies have been used to study infants' developing ability to discriminate among colors, shapes, faces, movement trajectories, and sounds (e.g., Cohen, Gelber, & Lazar, 1971; Perone & Oakes, 2006; Rakison, 2004; Rose, 1981). Habituation tasks have also been adapted in creative ways to study developmental change in general cognitive processes such as working memory (e.g., Ross-Sheehy, Oakes, & Luck, 2003), statistical learning (e.g., Kirkham, Slemmer, & Johnson, 2002; Saffran, Aslin, & Newport, 1996), category formation (e.g., Oakes, Coppage, & Dingel, 1997; Quinn, Eimas, & Rosenkrantz, 1993; Younger & Fearing, 2000), and the ability to associate labels with objects (e.g., Rost & McMurray, 2009; Werker, Cohen, Lloyd, Cassasola, & Stager, 1998).

Although looking measures have been widely used to study infant cognition for nearly half a century, interpreting looking can still be difficult. This difficulty has led to several key debates in the literature. For instance, Baillargeon (1987) has argued that young infants' limited behavioral repertoire precludes researchers from measuring high-level concepts that may be present very early in development. Baillargeon (1987) presented evidence that looking measures can tap infants' understanding of object permanence at 4 months of age, an ability previously believed to emerge at 10 to 12 months of age when studied in search tasks that require infants to reach for hidden objects. Other researchers have argued that looking indexes perceptually-based memory representations and have shown that looking changes dramatically as the stimulus and task context are manipulated (Bogartz, Shinskey, & Speaker, 1997; Cahson & Cohen, 2000; Haith, 1998). A richer understanding of how looking is linked to cognitive processing might resolve such debates.

Looking is clearly a powerful empirical tool. However, looking is also a critical exploratory behavior that mediates the interplay between the physical and social context and the developing brain. For instance, preterm infants explore more toys and more frequently shift their gaze among different toys when exploring objects in an environment shared with their caregiver than when they explore objects alone (Landry & Chapieski, 1987). Interestingly, individual differences in caregiver behaviors also affect how preterm infants behave. Caregivers who maintain their infant's attention on toys have infants who look longer at toys, explore more toys, and interact with the caregiver more. Critically, such directive behaviors of the caregiver can have a positive effect on cognitive development. Recent intervention studies that train caregivers to maintain their infant's attentional focus on objects have facilitated positive developmental outcomes in areas of language development and the coordination of joint attention (Landry, Smith, Swank, & Guttentag, 2008). Such interventions also affect the caregivers: mothers more frequently initiate joint attention and maintain their infants' focus after intervention than before (see also Landry, Smith, & Swank, 2006). These studies show that looking is not only a good measure of cognition but also contributes to change in cognition. Moreover, these studies point to a necessity of understanding the link between looking and cognitive dynamics across the second-to-second and developmental time scales on which infants explore and interact with objects and others. Such understanding might foster the assessment of cognition in the laboratory and interventions in the lives of at-risk infants.

The overarching goal of this thesis is to gain a richer understanding of how looking as an exploratory behavior is linked to cognitive dynamics as studied in the laboratory. I accomplish this goal by developing a new theoretical model of looking and memory formation and grounding its behavior in a rich empirical data set examining developmental change in looking, memory formation, and discrimination. Below, I present an overview of three literatures that capture how these behaviors and processes change over development. I begin with what is known about how looking dynamics and the rate of memory formation changes over development. Next, I discuss new insights into the link between looking and memory that have emerged from studying at-risk infant populations. Finally, I review what is known about how infants' discrimination abilities change over development. These three literatures set the stage for the specific goals I pursue in the thesis. Note that the literatures reviewed below will be brief. In subsequent chapters, detailed reviews will be presented where relevant.

Looking Dynamics and Memory

Looking and memory formation undergoes significant developmental change across the first year (for reviews see Colombo & Mitchell, 1990; Rose et al., 2004). Over the past several decades, three looking measures have emerged as reliable indices of developmental change in the rate at which infants form memories – shift rate (rate of switching gaze between pairs of stimuli relative to total looking time), look duration (average look length), and peak look (longest look). With age, shift rate increases, look duration decreases, and peak look decreases. It is widely accepted that these developmental changes reflect increases in the rate at which infant process and form memories for visual information. Rose, Feldman, and Jankowski (2002) have provided the clearest support for this hypothesis. They developed a preferential looking task where looking measures could be used as an index of processing speed. Infants were presented with pairs of 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 and was correlated with shift rate, look duration, and peak look.

There is some evidence that these looking measures are stable within individuals across development. Rose, Feldman, and Jankowski (2001) examined individual and developmental differences in a standard visual recognition task in which infants were familiarized with pairs of identical items and their memory for the familiar item was tested by pairing it with a novel one. As in the processing speed task, shift rate increased and look durations and peak looks decreased with age. Infants' novelty preferences also increased with age. Moreover, these looking measures were relatively stable across the first year – cross-age correlations showed that infants who exhibited a high shift rate at 5 months of age, for instance, also tended to exhibit a higher shift rate at 7 and 12 months of age. These looking measures were also associated with stronger novelty preferences within an age, which, presumably, measures the strength of infants' memory for the familiar stimulus. This study suggests, then, that individual differences in looking reflect differences in developmental state among infants.

Looking Dynamics and Memory In At-Risk Infant Populations

Researchers have gained new insights into the sources of individual differences in looking and cognitive dynamics by studying at-risk infant populations. The most commonly studied at-risk infant population is preterm infants. Prematurity puts children at risk for developmental delays in basic cognitive processes, special needs in the classroom, disabling conditions such as mental retardation, and diagnoses of childhood mental disorders such as Attention Deficit Disorder with Hyperactivity and Autism (Alyward, 2005; Biederman, Prince, Fischer, & Faraone, 2002; Larsson et al., 2005; Wilkerson, Volpe, Dean, & Titus, 2002). Many studies suggest that delays in basic cognitive processes are evident during infancy and may impact the development of higher-level cognitive function. These delays have been interpreted as delays in processing speed. The rational is that the adverse neonatal history of many premature infants impacts the neural processes underlying basic cognitive processes.

Overall, preterm infants' looking dynamics resemble those of younger term infants. Preterm infants exhibit slower shift rates, longer look durations, and weaker novelty scores than similarly aged term infants (Rose et al., 2001). These population differences in looking and recognition performance suggest that preterm infants are slower processors and form weaker memories than term infants. However, the looking measures on which term and preterm infants differ are not consistent across age and stimulus type. For example, Rose et al. (2001) found that at 5 and 7 months preterm infants exhibited a slower shift rate when looking at geometrical patterns but not faces. At 12 months of age, the opposite pattern was observed. Moreover, term and preterm infants do not always exhibit different patterns of looking and recognition performance. For example, Rose et al. (2002) found that term and preterm infants did not exhibit different patterns of looking in the processing speed task, although preterm infants were slower to meet the criterion than term infants. Similarly, Rose, Feldman, and Jankowski (2001b) found no differences in looking measures or recognition performance in a serial recognition task. The proposal in this thesis is that a richer understanding of how looking and cognitive dynamics are linked will shed light on this complex pattern of population differences across tasks and stimulus types.

Developmental Change In Discrimination

Over the course of the first year, infants' are able to make increasingly subtle discriminations along single, continuous metrically-organized dimensions. For example, Brannon, Sumarga, and Libertus (2007) examined changes in the precision with which infants discriminate a visual temporal duration over development. Six-month-old infants were able to discriminate a 1:2 temporal duration ratio, but not a 2:3 ratio. By contrast, 10-month-old infants dishabituated to a 2:3 temporal duration ratio, but not a 3:4 ratio. These findings suggest that infants' memory representations become more precise over development. Interestingly, the precision with which infants represent information also spans sensory modalities. Lipton and Spelke (2003) found that 6-month-old infants were able to discriminate 16 from 8 sounds, but not 12 from 8 sounds. Nine-month-old infants were able to discriminate 12 from 8 sounds but not 10 from 8 sounds. Together, these studies suggest that infants' memory representations become more precise during the first year.

These changes in discrimination are occurring during the same developmental period as changes in looking dynamics and recognition performance. It is unclear, however, whether changes in processing speed and discrimination are linked. Brannon et al (2007) found that older infants habituated more quickly than young infants and discriminated between highly similar familiar and novel stimuli. However, in a replication, they found no difference in habituation but a difference in discrimination still remained. It is notable that Rose et al. (2001) found that shift rate, peak look, and look duration were all related to recognition performance, which suggests that discrimination and processing speed are linked within individuals. However, Rose et al. used high-dimensional items that varied on multiple dimensions rather than items that have well-controlled metric properties required to study changes in discrimination abilities. A critical developmental question, therefore, is whether these two changes over development arise from the same or different mechanisms.

Goals of the Thesis

Looking is a powerful empirical tool for studying cognition during infancy. There is good evidence that looking dynamics index individual and developmental differences in processing speed. Additional evidence comes from studies of preterm infants, who exhibit looking and recognition performance that resembles younger term infants. Precisely how term and preterm infants differ, however, is at present unclear. There is no critical measure on which preterm and term infants consistently differ, and they do not always differ when their performance is compared across different stimulus types or tasks. During the same developmental period that looking is changing, infants are also exhibiting an increased ability to discriminate between similar items. It is unknown whether looking and discrimination change together over development and whether these changes arise from the same mechanism. Finally, there have been no studies examining how fine-grained discrimination changes over development in preterm infants.

The overarching goal of this thesis is to attain a richer understanding of the mechanisms that underlie changes in speed of processing and discrimination abilities during the first year. I will pursue this in three steps. First, my evaluation of current theories of infant habituation and visual recognition in Chapter 2 reveals that these theories offer a limited view of the link between looking and cognitive dynamics; thus, I propose a new dynamic field theory (DFT) in Chapter 3 that links the act of looking to the neural processes that underlie habituation and recognition. I then generalize this theory in Chapter 4 to a key task used to probe both speed of processing and visual discrimination—the visual paired comparison task—and I demonstrate the utility of the theory by generating and empirically testing a novel prediction.

The second step in this thesis pursued in Chapter 5 examines whether developmental changes in looking indices of processing speed and discrimination change together over development. Moreover, quantitative simulations of infants' behavior with the DFT probe whether both developmental changes can arise from a single mechanistic source—stronger neural interactions. The final step in this thesis probes whether the developmental course of discrimination in at-risk infants parallels that of typically developing infants, as looking measures do. This will foster a greater understanding of how typically and atypically developing infants differ, and whether speed of processing and discrimination abilities change together in both term and preterm populations.

In this thesis, I will argue that theory and experiment together can provide a deeper understanding of the link between looking and cognitive dynamics over development. In Chapter 2, I evaluate whether existing theories are up to this task.

CHAPTER 2

THEORIES OF INFANT LOOKING AND MEMORY

The empirical database from looking studies has grown immensely over the past several decades. During the same period, there have also been significant advances in theory. In this chapter, I review these theories. I begin with a review of conceptual theories of infant habituation. These theories have described how memory formation impacts looking, they have been empirically generative, and they have been generalized to at-risk populations. However, these theories are agnostic with respect to discrimination abilities. These theories, therefore, do not specify whether developmental change in processing speed and discrimination arise from the same or a different mechanism. Next, I review neural network theories. These theories describe how memory formation impacts looking well. They also describe the nature of memory representations, which enables them to capture developmental change in discrimination. Neural network accounts are also geared toward elucidating the neural dynamics that underlie looking, which may be useful in trying to understand how typically and atypically developing infants differ. Nevertheless, no single network architecture has been used to capture developmental change in discrimination and processing speed. Existing neural network theories, then, do not elucidate whether processing speed and discrimination arise from the same or a different mechanism. Finally, conceptual and neural network theories share a crucial limitation – they both treat looking as a behavioral output of cognitive dynamics instead of as the active behavior that it is. Indeed, experimental manipulations of how infants distribute their looks at a stimulus influences whether or not they recognize the stimulus

(Jankowski, Rose, & Feldman, 2001). This suggests that we need a better understanding of how the act of looking is linked to learning and memory formation in infant cognition.

Conceptual Theories of Infant Looking and Memory

Contemporary thinking about the processes underlying infant looking is still strongly influenced by Sokolov’s (1963) comparator model. Sokolov proposed that when an organism orients to a stimulus, it begins to construct an internal representation that is compared to the stimulus. As the internal representation and the stimulus begin to match, the organism orients away from the stimulus and seeks novelty. Although Sokolov’s comparator model is still influential, early work with infants showed that the model was incomplete. In one revealing study, Cohen (1972) found that orienting to a stimulus and sustaining fixation to the stimulus index separate, interacting processes. In particular, Cohen habituated infants to a small, medium, or large checkerboard that also varied in the number of checks. He found that infants exhibited longer looking to checkerboards with more, smaller checks than boards with fewer, larger checks. Interestingly, infants oriented more rapidly to larger stimuli than smaller stimuli, regardless of the number of checks.

Based on these findings, Cohen (1973) developed a dual-process model of infant habituation with two interactive processes: an attention getting process that controls orienting to a stimulus and an attention holding process that controls sustained looking at a stimulus. The thrust of the model was that stimulus properties such as brightness and size attract infants’ gaze, but, once fixated, perceptual encoding and memory formation sustain 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. The dual-process model enriched Sokolov's basic comparator process, delineating multiple interactive processes that orient gaze, sustain fixation, and release fixation from a stimulus.

The basic processes described in the dual-process model are the foundation for more recent conceptual theories of infant habituation. Most notable is Hunter and Ames' (1988) multi-factor model. The core assumption of the model is that early in learning, infants actively encode a stimulus, which biases them to preferentially look at familiar over novel stimuli. Familiarity preferences, thus, reflect the active encoding and initial memory formation that underlies attention holding in the dual-process model. Late in learning, infants' memory for a stimulus supports recognition and biases them to look at novel over familiar stimuli. The transition from familiarity-to-novelty is assumed to be gradual, resulting in null preferences in between that reflect an equal influence of memory for the familiar stimulus and encoding of the novel one.

A central innovation of the multi-factor model is that it captures the familiarity-to-novelty shift. In this theory, the time course of this shift can vary with the developmental state of the infant. Indeed, young infants exhibit familiarity preferences after longer periods of familiarization than older infants, indicating that young infants form memories for visual information more slowly than older infants (Rose, Gottfried, Melloy-Carminar, & Bridger, 1982).

In summary, the dual-process (Cohen, 1973) and multi-factor (Hunter & Ames, 1988) models remain the overarching framework for investigations of the processes underlying looking and have consistently been supported by empirical findings. These models do have some important limitations, however. One limitation is that they do not specify how developmental changes in looking and memory processes arise. For instance, the multi-factor model does not explain why stimuli are recognized with less exposure over development or why looking dynamics differ across individuals and development. One explanation is that infants process information more quickly with age, allowing them to form memories more quickly which, in turn, leads them to look less. Indeed, this *processing speed hypothesis* is the most popular framework in which looking measures are interpreted (see Rose et al., 2004 for a review). For example, the notion of processing speed generalizes to individuals – infants who exhibit more mature looking dynamics are faster processors than infants who exhibit less mature looking dynamics. And the concept generalizes to at-risk infant populations - preterm infants exhibit looking dynamics that resemble younger infants because they are slower processors. A major limitation of the processing speed hypothesis, however, is that it does not explain *how* processing speed changes. For example, does processing speed change because the time required for a stimulus to be encoded gets faster, that the time it takes to consolidate an item in working or long-term memory gets faster, or both? And how do such changes arise in the infant brain? Neural network theories have offered new insights into possible mechanisms underlying developmental change in processing speed. I turn to these theories next.

Neural Network Models of Infant Looking and Memory

During the past decade, neural network models have begun to elucidate the neural processes that underlie developmental changes in looking, memory formation, and recognition performance during infancy. All existing models implement a common notion of looking, shown in Figure 1A. In this implementation, looking is a behavioral output of processing within the cognitive system. As infants experience a stimulus, they begin to construct an internal representation of it. This leads to high levels of looking. Over time, the representation begins to match the stimulus in the world. This leads to low levels of looking. Below, I will review the accomplishments and limitations of three common classes of neural network models: autoencoders, autoassociaters, and dynamic neural fields.

Autoencoders. A long-standing debate in the infant cognition literature is whether infants rely on conceptual or perceptual information to group items into categories in habituation tasks. Autoencoders have made a major contribution to this debate. Autoencoders consist of a small layer of hidden nodes sandwiched between larger, identical input and output layers. Each input and output node is tuned to a different feature of, for instance, an animal (e.g., has legs) or a feature value of a dimension (e.g., leg length). As the network is trained with an input pattern, the hidden layer gradually learns to reproduce the input pattern on the output layer. Looking time is approximated by calculating the error between the input and output vector, which is high early in training and low late in training. This is said to result in longer looking at the onset of training and shorter looking at the end of training. The network recognizes a novel stimulus if the input pattern can be reproduced relatively well at test (i.e., low error), and the network detects a novel stimulus if the input pattern cannot be reproduced (i.e., high error).

Autoencoders have been particularly fruitful in describing the categorical representations infants' form in looking tasks. A well-studied example is the finding that 4-month-old infants familiarized with pairs of dogs included cats in their dog category, but 4-month-old infants familiarized with cats excluded dogs from their cat category

(Quinn et al., 1993). Networks trained with a distribution of feature values derived from the stimulus set used by Quinn and colleagues exhibited the same asymmetry (French, Mareschal, Mermillod, & Quinn, 2004). A series of simulation studies suggested that the scope of infants' categories depends on the statistical distribution of feature values to which they are exposed during familiarization. In particular, simulation studies showed that the variability of the dog feature values (e.g., ear width) was considerably broader and encompassed the variability of the distribution of cat feature values. Importantly, constraining the distribution of dog feature values and expanding the distribution of cat feature values reversed the asymmetry in both networks and infants.

Although generative, autoencoders have some limitations. Standard autoencoders are limited in their ability to capture developmental changes in stimulus representations because they are dominated by the statistical distribution of the input. In the asymmetrical category learning example described above, a standard autoencoder learns an asymmetrical category when the distribution of one category encompasses the other and a symmetrical category when the distributions of feature values do not overlap. Infants, by contrast, show different patterns depending on their developmental state. For example, in contrast to 4-month-olds, 10-month-olds differentiate cats from dogs when familiarized with the stimulus set used by Quinn et al. (1993) with an encompassing stimulus distribution (Furrer and Younger, 2005).

Can autoencoders capture this developmental change? Westermann and Mareschal (2004) showed that this might be possible by creating more precise stimulus representations with age. They proposed that the tuning of receptive fields in early visual processing pathways might become more precise over development. In an autoencoder, the connections between the hidden layer and the input and output layers can be implemented as receptive fields. These receptive fields can be narrowed to reduce overlap among connections. This decreases the probability that a novel stimulus will excite neurons tuned to a familiar stimulus. Westermann and Mareschal showed that more precise feature representations can capture developmental change in infants' relational-based category learning. Although this is an intriguing concept, it is unclear what mechanism would underlie such tuning changes.

Another limitation of autoencoders is that they do not capture the familiarity-to-novelty shift evident in some empirical studies with infants (French et al., 2004). A different type of network, the autoassociator, does capture familiarity effects. I turn to this class of neural networks below.

Autoassociators. An autoassociator consists of a single bank of interconnected nodes, and, like autoencoders, learns to reproduce an input pattern (see Sirois, 2004 for a review). The input to each node is a single feature value of a stimulus, such as a pixel in an image of a human face. Over a number of iterations, the model learns to reproduce the input pattern.

Sirois and Mareschal (2004) used an autoassociator to construct a model of infant habituation. The model—HAB (for Habituation, Autoassociation, and Brain)—consisted of coupled cortical and hippocampal autoassociative networks sandwiched between identical input and output layers. In this interacting systems model, input is relayed through a bank of thalamic neurons to the cortical network and the hippocampal network. The cortical network learns to reproduce the input while the hippocampal network learns to selectively inhibit known input. The cortical and hippocampal networks are also connected to a bank of output nodes that represent the same feature values as the input nodes. HAB effectively captured the familiarity-to-novelty shift from the preferential looking paradigm. HAB also captured developmental change in the rate at which infants shift from a familiarity to a novelty preference by strengthening the connection weights from the cortical to hippocampal network as well as the connection weights from the cortical network to the output layer. This effectively produced an increase in processing speed. Thus, a major accomplishment of HAB is that it describes how developmental changes in processing speed might emerge. It is notable that with training, an increasingly smaller number of nodes within autoassociators become capable of recognizing an entire stimulus pattern distributed across nodes. In this sense, processing a stimulus and representational precision happen together. It is unclear whether this feature of autoassociators, such as HAB, enables them to simultaneously capture developmental change in processing speed and discrimination in infant visual recognition tasks.

Dynamic Neural Fields. Autoencoders and autoassociators are quite good at capturing the link between the stimulus context and looking, but they have not captured the link between the task context and looking. To take a step in this direction, Schöner and Thelen (2006) used a different class of models – Dynamic Neural Fields (DNFs). DNFs consist of layers of neurons organized by functional topography such that each neuron responds maximally to a preferred stimulus and less robustly to similar stimuli. Typically, DNF models consist of reciprocally coupled layers of excitatory and inhibitory neurons. The evolution of neuronal activation in these layers over time captures the evolution of behavioral decisions to, for instance, fixate a stimulus.

Schöner and Thelen (2006) proposed a simple DNF model that consisted of a collection of similarly tuned excitatory and inhibitory neurons sampled from sites along a continuous metric dimension (e.g., color). In this model, each excitatory neuron was maximally excited by a particular feature value (e.g., blue) and partially excited by similar feature values (e.g., aqua). Suprathreshold activation in the excitatory layer drove looking and also drove the buildup of activation in an inhibitory layer, which evolved over a slower time scale. As a stimulus was repeatedly presented to the model, inhibitory activation accumulated, suppressing activation in the excitatory layer and producing habituation. The model dishabituated when a novel stimulus activated a relatively uninhibited excitatory neuron.

The DNF model was intentionally simple. Despite this, it accounted for a complex empirical data set thought to reflect the precocious knowledge of young infants. This highlighted that infants' performance in looking tasks emerges from interactions between the developmental state of infants, the task context, and the stimulus context. An important limitation of the DNF model, however, is that it captures habituation dynamics via an inhibitory long-term memory and retains no excitatory memory for stimuli experienced during habituation. Although inhibition is certainly involved in habituation, learning in looking tasks reflects excitatory long-term memory formation and knowledge acquisition (see Oakes, Horst, Kovack-Lesh, & Perone, 2008; Sirios & Mareschal, 2004).

Summary of Theoretical Survey and the Need for a New Theory

Although the three classes of neural network models reviewed above move beyond earlier conceptual theories, they share three limitations that a theory of infant looking and memory formation must overcome to achieve a richer understanding of the link between looking and cognitive dynamics. The first limitation is that these models assume memory formation is a gradual, continuous process. This assumption stems from the finding that infants exhibit a familiarity preference after brief periods of familiarization, a null preference after longer familiarization lengths, and a novelty preference after prolonged exposure. Roder, Bushnell, and Sasseville (2000; see also Colombo, Mitchell, & Atwater, 1990), however, proposed that the gradual transition from familiarity to novelty is an artifact of averaging across infants. More specifically, they proposed that individual infants do exhibit a familiarity preference early and a novelty preference late in learning, but variation in the time course of the familiarity-to-novelty shift across individuals is responsible for null preferences at the group level. Indeed, they found that infants rarely exhibited a null preference between familiarity and novelty preferences. Instead, the transition from exhibiting a familiarity preference to exhibiting a novelty preference occurs as quickly as from one trial to the next. This finding suggests that memory formation transitions from an encoding phase to a memory phase non-linearly. A theory of infant looking and memory needs to explain how non-linear transitions in looking arise.

The second limitation of these models is that they have not captured developmental change in processing speed and discrimination within the same system. These models, then, do not specify whether change in these abilities arise from the same or different mechanism. Historically, models have been special purpose – designed to capture one empirical data set. Thus, while one architecture and process is used to capture developmental change in processing speed, such as Sirois and Mareschal’s (2004) HAB, another architecture is used to capture developmental change in discrimination, such as

Westerman and Mareschal's (2000) autoencoder. This provides only a limited view of the central question tackled in this thesis: do developmental changes in processing speed and discrimination arise from the same or different mechanism? Probing this question requires that both phenomena be captured by a single architecture.

The last and perhaps most crucial limitation of these models is that they all treat looking as a behavioral output of cognitive processing instead of as the active behavior that it is. This is not consistent with evidence that looking actively structures learning: *studies that directly manipulate how infants distribute their looks through time change what infants learn*. Across two critical experiments, Jankowski et al. (2001) showed that how an infant looks at a stimulus affects memory formation, recognition, and novelty detection. 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. showed that infants who exhibited long looks during the pretest phase *and were induced to exhibit short looks during the familiarization phase* recognized the stimulus and exhibited a novelty preference. To induce short looks, a light was illuminated in a different quadrant once every second during familiarization. Thus, an experimental manipulation of how infants distribute their looks affected memory formation, recognition, and novelty detection. Theories of infant looking and memory must, therefore, capture the contribution of looking to memory formation while also capturing the reliable nature with which looking indexes cognitive processes.

How might this challenge be met? A series of recent studies has examined looking as an interesting exploratory behavior in its own right and shed new light on looking as an active behavior. To capture the exploratory dynamics of infant looking and looking away, Robertson, Guckenheimer, Masnick, and Bacher (2004) proposed a simple dynamical systems model. The model consisted of a single bi-stable unit that, when above zero, was said to be looking and, when below zero, 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-old infants situated in front of an array of toys including the transition rate between looking and looking away, look duration, and look away duration. This implementation of looking is shown schematically in Figure 1B. Here, looking is an exploratory system and the second-to-second dynamics of looking emerge from a confluence of factors that can include content in the world (e.g., stimuli in the task space) and the intrinsic dynamics of the looking system itself (e.g., noise, bias).

In Chapter 3, I will propose a new dynamic systems theory of infant looking and memory formation that combines the insights from conceptual and neural network models with the work of Robertson and colleagues. The general theoretical proposal is pictured in Figure 1C. Here, looking is one component of an autonomous, dynamic exploratory system that learns by actively behaving in an environment in real time. The infant experiences the world by looking at it, and the maintenance or release of fixation depends on the content of the world and the state of the infant's cognitive system at that moment in time. I formally build this exploratory system using dynamic neural fields. I show that this model overcomes the three limitations of existing neural network models – it captures non-linear changes in memory formation, specifies the mechanisms that underlie processing speed and discrimination within a single system, and links exploratory looking to cognitive dynamics.

My theory shares core concepts with the conceptual and neural network theories described above. In particular, all theories of infant looking and memory posit that memory formation happens over time and that memory formation for a stimulus enables infants to recognize it and seek novelty. However, my theory is committed to a different view of looking than existing conceptual and neural network theories. In my theory, looking is an active behavior that acts as a perceptual gate into the cognitive system. In this way, the temporal dynamics with which input is given to the cognitive system for processing is controlled by the act of looking and not the mere presence of a stimulus in the task space. This theoretical commitment is closely tied to a particular formal implementation. I implement looking as a stochastic, dynamical system in the spirit of Robertson et al. (2004), who were able to capture the temporal dynamics of infants' looking and looking away. In my theory, a bias to look and look away emerges from a second commitment centered on the interaction between a perceptual system that encodes stimuli and a working memory system that maintains information about the stimulus. In particular, a bias to look arises from neural activity associated with encoding of a stimulus. A bias to look away arises from the emergence of robust memory that suppresses encoding. This resembles the attention-holding process of Cohen’s (1973) dual-process model. However, the dual-process model was descriptive. In Chapter 3, I examine whether formally implementing active, stochastic looking and an attention-holding process in a DNF model leads to novel insights about infant looking and memory.

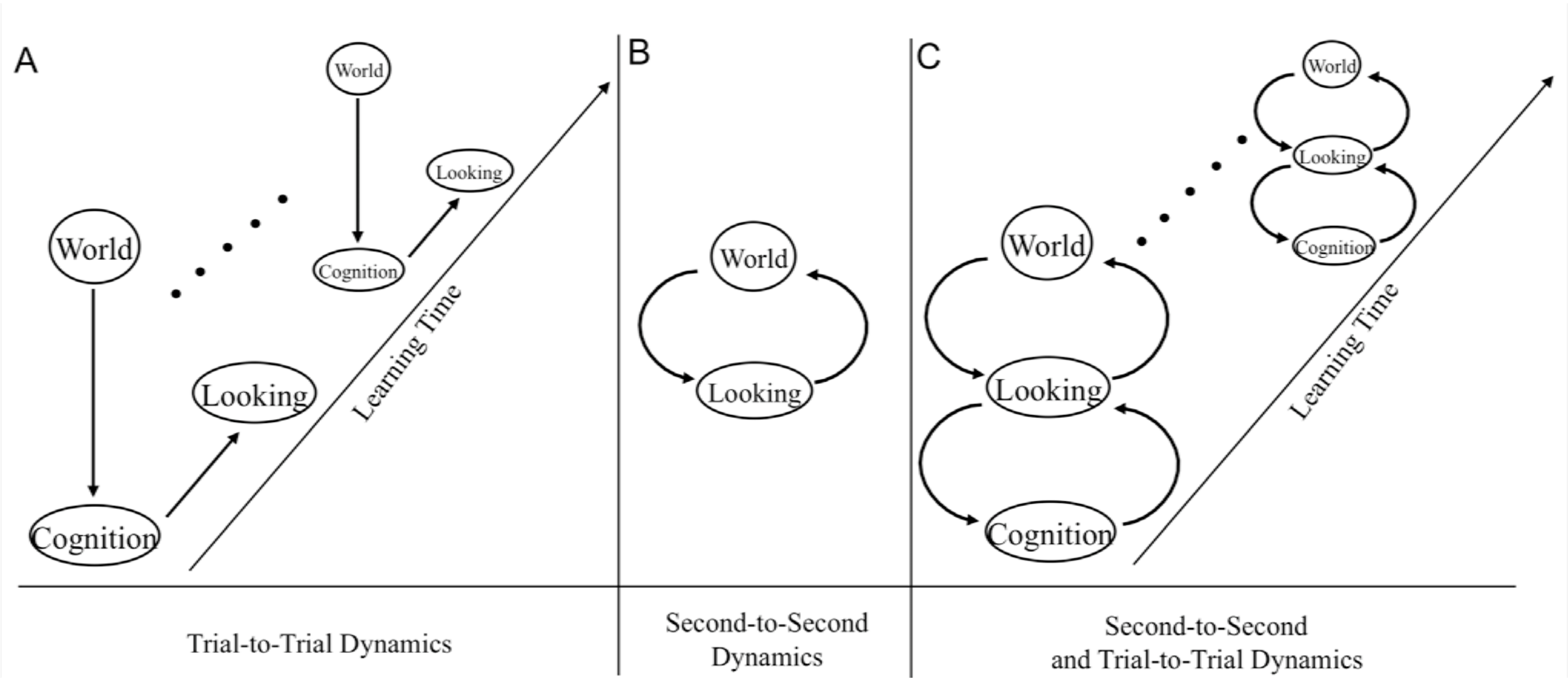


Figure 1. Three Implementations of Looking. Looking as a behavioral output of cognitive processing over time (A). Here, the world is input into the cognitive system and looking a direct index of processing and representation. This system captures the trial-to-trial dynamics of learning. Looking as a stochastic dynamic system that looks at the world (B). This system captures the second-to-second dynamics of looking and looking away. 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 (C). This system captures the link between the second-to-second dynamics of looking and the trial-to-trial dynamics of learning.

CHAPTER 3

A DYNAMIC SYSTEMS THEORY OF INFANT LOOKING AND MEMORY FORMATION

Dynamic systems theory is a general set of concepts that describe behavior as the organization of multiple, interacting components over time around attractor states. There are three broad systems concepts that have been applied to the study of cognition and development (for a discussion, see Smith & Thelen, 2003). These concepts capture infant looking and memory well. First, time scales are continuous with each other. For instance, the second-to-second looking behavior of an infant is continuous with looking dynamics over the learning and developmental time scales. Second, multiple factors influence the behavior of a system. The task context, stimulus context, history of experience, and developmental state of the infant all influence how infants look and remember in real time in the laboratory. Lastly, systems are open to the environment in which they behave. Looking appears to be a gate through which the environment influences cognition. This might be the very reason why looking is such a powerful behavior for caregivers of at-risk infants to act upon—it is the gateway through which positive changes in basic social and cognitive abilities can emerge.

One challenge in applying systems concepts to the study of cognitive development is specifying the system components and attractor states under study. The dynamic field theory (DFT) has emerged to meet this challenge. The DFT is a set of systems concepts that capture embodied cognitive dynamics (for reviews see Schöner, 2009; Spencer, Perone, & Johnson, 2009; Spencer, Simmering, Schutte, & Schöner, 2007). A central goal of the DFT is to specify the link between sensorimotor experience and cognition. This goal has been achieved by formalizing systems concepts in dynamic neural field (DNF) models. DNFs belong to a larger class of bi-stable attractor networks (Amari, 1977; Wilson & Cowan, 1972). Such models have been used previously to capture the mapping between real-time neural dynamics and behavior in a variety of domains including the planning and execution of eye movements (Kopecz & Schöner, 1995; Wilimizig, Schneider, & Schöner, 2006), the planning of reaching movements (Bastian, Schöner, & Riehle, 2003), visual working memory for features (Johnson, Spencer, & Schöner, 2009; see also Johnson, Spencer, Luck, & Schoner, 2009), and spatial working memory (see Spencer et al., 2007 for a review). DNFs have also effectively captured the co-development of neural and behavioral processes in the Piagetian A-not-B task (Thelen et al., 2001) and spatial working memory tasks (Schutte & Spencer, 2009; Schutte, Spencer, & Schöner, 2003; Simmering, Schutte, & Spencer, 2008). These previous applications demonstrate that DNFs provide an effective set of concepts that link cognition and behavior in real-time, over learning (e.g., Lipinski, Simmering, Johnson & Spencer, 2010; Lipinski, Spencer, & Samuelson, 2010), and over development (e.g., Schöner & Thelen, 2006).

In this chapter, I propose a DNF model that captures the link between looking and cognitive dynamics. The model is based on a model of visual working memory and change detection proposed by Johnson et al. (2009). In their model, multiple items (e.g., colored squares) are encoded in parallel. Encoding generates a working memory representation that can be 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. By contrast, new items have stimulus values that fall outside of the inhibited stimulus regions. This results in the formation of a new perceptual representation and the system detects the novelty.

To capture infant looking and memory formation, two additions to this model were needed. First, a form of Hebbian learning (see Lipinski et al., 2010; Spencer, Dineva & Schöner, 2009) was added that enables the model to respond more robustly to previously encoded items and facilitates working and long-term memory formation. Second, a fixation system was added that looks and looks away from locations at which task relevant stimuli appear, opening a perceptual gate into the encoding and working memory system.

Central Concepts of Dynamic Neural Fields

A DNF consist of layers of neurons organized by functional topography along continuous, metric dimensions (e.g., color). Neuronal activation in DNFs is based on the space code principle from neurophysiology in which neighboring neurons mutually excite each other. In addition, locally excited neurons stimulate similarly tuned inhibitory interneurons which implement a form of lateral or surround inhibition. This 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 and the inputs impinging on them. Amari (1977) originally analyzed five qualitatively different attractor states that DNFs can enter. Below, I describe three of those states and their cognitive function in the context of infant looking and memory formation.

The first attractor state that DNFs can enter is the resting state in which neuronal activation stably rests at a baseline level of activity. The DNF proposed here 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 selectively tuned neurons create a localized peak of activity in response to stimulus properties. This peak is a perceptual representation of a stimulus at the level of the neural population. Critically, a self-stabilized peak can only maintain suprathreshold levels by the continued presence of input (see, e.g., Johnson et al., 2009).

Figure 2A-E illustrates how the self-stabilized state reflects a form of perceptual encoding. It also illustrates how Hebbian learning can influence encoding at recently stimulated sites. Across panels A-E, a stimulus (see top row) is presented to an excitatory layer of neurons shown in row two. I will refer to this layer of neurons as a perceptual field (PF). Initially, no stimulus is present in Figure 2A (see top row). Consequently, PF is in the resting state. When a stimulus is presented (2B), it excites selectively tuned neurons in PF. When neurons in PF are suprathreshold (i.e., above zero), they project excitatory input to a narrow range of neighboring neurons. They also project to a narrow range of similarly tuned neurons in an Inhibitory layer (Inhib; not shown for simplicity), which, in turn, project broad inhibition back to PF. This creates a peak with a locally excitatory / laterally inhibitory activation profile (2B). This peak of activation leaves a trace in a Hebbian layer (HL_{PF}), which effectively raises the baseline level of activity at previously excited sites and enables those neurons to respond more strongly upon representation of the stimulus (compare B and D). The light gray bump of activation at the bottom of the x-axis shows the contribution of HL, the strength of which is represented on the right y-axis.

When local excitatory / lateral inhibitory interactions are stronger, DNFs can enter the self-sustaining state in which recurrent local excitatory connections are sufficiently strong to maintain activation peaks in the absence of stimulation. This attractor state has been used to capture the maintenance of information in working memory (Johnson et al., 2009; Schutte & Spencer, 2009; Simmering, 2008; for related models, see Compte, Brunnel, Goldman-Rakic, & Wang, 2000; Edin, Macoveanu, Olesen, Tegner, & Klingberg, 2007) and is generally consistent with findings showing that neurons exhibit elevated levels of discharge during delays (Funahashi, Bruce, & Goldman-Rakic, 1989).

The self-sustaining state is illustrated in the bottom row of Figure 2. Across panels F-J, the stimulus shown in the top row is presented to an excitatory layer of neurons as before. Now, however, I have labeled the field in the bottom row as a working memory (WM) layer to reflect the stronger neural interactions. Initially, no stimulus is present and WM and Inhib (not shown) are in the resting state (2F). When a stimulus is presented, WM enters the self-stabilized state (2G), and, as before, activation returns to its resting level when the stimulus is removed (2H). When the stimulus is presented again, the contribution of the Hebbian layer (HL_{WM}) is sufficient for WM to enter the self-sustaining state. Consequently, a peak of activation is built (2I) that is maintained even though the stimulus is removed in panel J—the field maintains a working memory for the stimulus in the absence of external stimulation.

The 3-layer+ Model

The DNF model I propose takes as its starting point the 3-layer model proposed by Johnson et al. (2009) to capture visual recognition and change detection in adults. The one central difference is that visual recognition in infancy unfolds over a slower time scale; consequently, learning processes play a more central role in the formation of visual preferences in infancy. The basic concepts behind this model are shown in Figure 3. This figure shows a simulation of the 3-layer architecture from Johnson et al. (2009) with a Hebbian layer added to PF and WM (HL_{PF} and HL_{WM}). The second row shows PF with relatively weak neural interactions, and the bottom row shows WM with stronger neural interactions. These two layers are coupled to a shared layer of inhibitory interneurons (Inhib), which is not shown for simplicity. As in Johnson et al., input (see top row) is passed strongly into PF and weakly into WM. In addition, above-threshold activation in PF stimulates similarly tuned excitatory neurons in WM (see blue arrow from PF to WM). Finally, the light gray line (right y-axis) shows the contribution of Hebbian learning to both layers.

When a stimulus is presented to the 3-layer+ model, a self-stabilized peak arises in PF, encoding the stimulus and propagating strong excitation into WM (3A). When the stimulus is removed, a stable WM peak maintains a representation of the stimulus in its absence (3B). Notice that the maintenance of a stable WM peak inhibits similarly tuned neurons in PF via the shared layer of inhibitory interneurons (the red dashed arrow highlights this functional connection). When an identical stimulus to the one being maintained in WM is presented, activation in PF is relatively weak (3C). *This* *suppression of encoding is the mechanism of visual recognition in the model*. When a novel stimulus is presented, by contrast, it excites neurons in PF that are relatively uninhibited and a self-stabilized peak emerges (3D). *This is the basis of novelty detection in the model*. Note that once the new peak emerges in PF, a new peak is added in WM as well; thus, this model captures the continual dialog between perceptual encoding and working memory formation.

Below, I provide a more detailed overview of the 3-layer+ model.

Perceptual Field (PF). The equation for PF is:

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

where $\dot{u}(x,t)$ is the rate of change of activation for each excitatory neuron across the continuous behavioral dimension (e.g., color), x, as a function of time, t, and τ_{excite} is the time constant along which activation evolves. The time constant, τ_{excite}, of the excitatory layer was fixed at 80 for all simulations here. 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:

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

with its position centered at x_{center}, width σ, and strength c. The gating function, $X(t)$, denotes that the stimulus input is weighted with a 1 during time intervals when the stimulus is "on" and 0 otherwise.

The neural dynamics within PF are also influenced by excitatory within-layer neural interactions, $\int c_{uu}(x-x')\Lambda_{uu}(u(x',t))dx'$. 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 non-linear sigmoidal threshold function, $\Lambda_{uu}(u(x',t))$, which dictates that only neurons with above-threshold activation participate in the locally excitatory interactions. The width of this neural neighborhood is relatively narrow. The sigmoidal function is specified by:

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

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

In addition to local excitatory interactions, the neural dynamics in PF are influenced by inhibition, $\int c_{uv}(x-x')\Lambda_{uv}(v(x',t))dx'$. This inhibition is generated by the activity of neurons in the 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, $\Lambda_{uv}(v(x',t))$, contribute to interactions. In contrast to within layer excitatory neural interactions, the width of this neural neighborhood is broad. The cross-layer interaction, then, gives rise to a locally excitatory / laterally inhibitory activation profile.

Activation in PF is influenced by input from a Hebbian layer, $\int c_{uhl}(x,x')hl_u(x,t)dx'$. This input is determined by the convolution of a Gaussian projection, $c_{uhl}(x,x')$, which determines the neural neighborhood across which Hebbian traces have an influence, and the strength of the trace within the Hebbian layer, $hl_u(x,t)$ (see equation 7).

Finally, activation in PF is influenced by the addition of spatially correlated *noise*:

$$q\int g_{noise}(x-x')\xi(x',t)dx'$$

Noise was presented to PF by convolving a field of white noise, $\xi(x',t)$, with a Gaussian kernel, $g_{noise}(x-x')$. In spatially correlated noise, the strength of noise introduced to one neuron is linked to the strength of noise of a neighboring neuron

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

$$\begin{gathered}\tau_{inhib}\dot{v}(x,t) = -v(x,t) + h_v \\ + \int c_{vu}(x-x')\Lambda_{vu}(u(x',t))dx' \\ + \int c_{vw}(x-x')\Lambda_{vw}(w(x',t))dx' \\ + \textit{ noise} \qquad (5)\end{gathered}$$

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 was added to the inhibitory layer (see equation 4).

Working Memory Field (WM). The excitatory layer of the WM(*w*) field is specified by the following equation:

$$\begin{aligned}\tau_{excite}\dot{w}(x,t) = -w(x,t) + h_w + cS(x,t) \\ +\int c_{ww}(x-x')\Lambda_{ww}(w(x',t))dx' \\ -\int c_{wv}(x-x')\Lambda_{wv}(v(x',t))dx' \\ +\int c_{wl}(x,x')l_w(x,t)dx' \\ +\int c_{wu}(x-x')\Lambda_{wu}(u(x',t))dx' \\ + noise \qquad (6)\end{aligned}$$

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. Thus, WM received weak direct input, consistent with Johnson et al. (2009). 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.

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

$$\dot{hl}_u(x,t) = \begin{cases} \frac{1}{\tau_{build}}\left[-hl_u(x,t) + \Lambda_{hlu}(u(x,t))\right] & \text{if } u(x,t) \geq 0 \\ \frac{1}{\tau_{decay}}\left[-hl_u(x,t)\right] & \text{otherwise} \end{cases} \qquad (7)$$

where $\dot{hl}_u(x,t)$ 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 the Hebbian layer only accrues when neurons in PF are above threshold, $u(x,t) \geq 0$. τ_{build} was set to 10,000, and τ_{decay} was set to 50,000.

Fixation System

Fixation System: The 3-layer+ model described above captures the perceptual, working memory, and long-term memory processes hypothesized to underlie memory formation, visual recognition, and discrimination in infancy. The next step is to specify the process that underlies fixation dynamics in infancy. 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. 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:

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

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 also has a self-excitatory component that creates bi-stable switching between an "off" state and an "on" state over time. This non-linear behavior is mediated by the 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 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}.

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

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

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 (i.e., above zero), 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 type of bias helps create a stochastic, oscillatory pattern of looking ("on") and looking away ("off") through time.

Figure 4 shows the behavior of the fixation system over a 20 s period. Figure 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 over time (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. The attention-getting stimulus is approximated 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. When a stimulus is present on the display (e.g., within a habituation trial), a noisy low-level input is 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.

While in the looking state, there are two ways in which the fixation system can re-enter the looking away state. One source is random fluctuations in noise that spontaneously drive the fixation system below threshold. A second source is the dynamic modulation of the resting level. Strong activation in the fixation system dynamically drives the resting level to its low attractor. As the resting level decreases, the self-excitatory dynamics of the fixation system are insufficient to maintain above-threshold activation. Once the fixation system is below threshold and looking away, the system dynamically returns to its higher resting level, facilitating the shift back into the fixation state (via noise, input, and self-excitatory dynamics).

As can be seen in Figure 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 simple dynamical 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 this fixation system and the one used by Robertson et al. First, the noise within this system is introduced via noisy input, whereas noise in their system was intrinsic. These types of noise differ only during the inter-trial interval when no task relevant input is present in the task space. The use of noisy inputs was 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 et al., 2008). Second, hysteresis within this fixation 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 (2004) model, hysteresis was introduced with a small bias to remain in the recently entered state.

The Integrated Architecture

Coupling the fixation system to the 3-layer+ model creates an autonomous exploratory system that encodes and forms memories of a stimulus as it looks. The fixation system acts as a perceptual gate into the neural system such that encoding of a stimulus, and, reversely, the contribution of encoding to fixation, is only possible when the fixation system is actively looking at it. Gating was accomplished by modifying the inputs to PF (see $S(x,t)$ in equation 1) and WM (equation 6) with the thresholded activation of the fixation system, that is, $S(x,t)$ was replaced by $S(x,t)\Lambda(\mathrm{f})$. Support for fixation while encoding a stimulus was accomplished by feeding the weighted sum of activation in PF into the fixation system. This integration can be seen in a modified equation 8:

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

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.

Figure 5 illustrates how the DNF model autonomously encodes and forms a memory as it looks at and looks away from 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 as it looks at and looks away from the stimulus (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 (see 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 of PF and WM that underlie these looking dynamics are shown in Figures 5D-H, which shows the state of these fields at different points during familiarization (30s, 40s, 88s, 96s, and 160s). Figure 5D shows the state of PF and WM as well as the long-term memory contributions as the model looks at the stimulus early in learning. Activation in PF is strong and a peak in WM is beginning to emerge. The robust peak in PF helps support the long look by the fixation system around 30 s (see C). Figure 5E shows the state of PF and WM while the model is looking away early in learning (at 40 s; see C). Activation in PF and WM has returned to sub-threshold levels after the fixation system spontaneously looked away.

As the model continues to look at and look away from the stimulus, the contribution of HL_{WM} to WM increases (F). Consequently, when the model looks away from the stimulus at 96 s (G), a WM peak has emerged, producing strong inhibition in PF (see inhibitory trough in PF in panel G). This inhibition, in turn, suppresses the formation of a peak in PF when the model looks at the stimulus again late in learning (H). This suppression of encoding quickly releases fixation, look durations become short, and the model accumulates more time looking away. The model habituates to the stimulus.

Below, I present a set of simulations that illustrate the processes of habituation and dishabituation in a single presentation habituation task. A theory of infant looking and memory needs to capture infant looking behavior in a particular task and stimulus context. In Chapters 4 and 5, I show that the DNF model is up to this challenge. Here, my simulations aimed to illustrate the basic theoretical concepts of the DFT of infant looking and memory formation by capturing a set of established empirical facts from the infant habituation literature. In particular, I focused on empirical results that show developmental changes in looking, memory formation, and discrimination. With age, infants form memories more quickly, which is associated with faster habituation, less looking time accumulated across the habituation phase, and a decrease in look duration (e.g., Rose et al., 2001; Rose et al., 2002; Wetherford & Cohen, 1973; for reviews, see Colombo & Mitchell, 1990; Rose et al., 2007). With age, infants also exhibit an increased ability to discriminate between similar familiar and novel items, that is, with age infants dishabituate to both similar and dissimilar novel items (e.g., Brannon et al., 2006; 2007).

Simulation results were based on 200 simulations of the same parameter settings. Preliminary simulation work demonstrated that 200 simulations per set was sufficient to produce replicable simulation results in the presence of random fluctuations across simulations and capture the stable dynamics of the system specified by the parameter settings. Trial durations were 20 s and inter-stimulus intervals were 5 s. 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 habituation stimulus was presented across 10 trials followed by one test trial with the close test and one with the far test. I illustrate the basic concepts of habituation and dishabituation using a parameter set that will be referred to as the “old infant model”. After that, I will show how the DNF model captures developmental change in habituation and dishabituation. Model parameters are listed in Table 1.

Mechanisms of Habituation and Dishabituation

In the DNF model, looking habituates as a stimulus is encoded and a stable WM peak is formed across successive presentations. Figure 6 illustrates this process. When the model looks on trial 1, activation in PF is strong and the model begins to accumulate activity in HL_{PF} (A). Strong activation in PF supports looking, leading to few looks, long look durations, and high levels of total looking time. By trial 4 (C), the model forms robust peaks in both PF and WM. Consequently, Hebbian learning associated with WM increases in strength. This has two consequences. First, excitation in WM produces stronger activation of the inhibitory interneurons in Inhib, which begins to suppress activation in PF. This is evident by trial 4 (see inhibitory trough around stimulus site 150 in panels C and D). Consequently, PF provides weaker excitatory input to the fixation system over trials, and the model encodes the stimulus for increasingly shorter durations. This causes look durations and looking time to decrease over trials. Second, the activation increase in WM causes a stable WM peak to emerge. This enables the system to maintain a representation of the stimulus in the absence of looking and during inter-stimulus intervals. For instance, there is a WM peak in the bottom panel of Figure 6D even though no stimulus is present during the ISI. This stable WM peak impacts activity in PF upon subsequent trials. For instance, in Figure 6E, even though the model fixates the stimulus, activity in PF is weak due to the strong inhibition generated by WM.

To highlight the stable dynamics of the system as specified by the parameter settings, Figure 6G shows the mean state of PF and WM across the entire simulation set at the onset of each habituation trial. When the model begins each trial early in learning, the contribution of HL_{PF} to PF facilitates encoding (see dashed blue line in top panel of G). Late in learning, HL_{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 and establishes a relatively weak peak in PF. 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. In Figure 6G, this transition can be seen in the activation profile between trials 4 (dashed red line) and 5 (solid purple line) when, on average, the model acquires a stable WM peak and inhibition in PF becomes relatively strong.

The looking behavior of the old infant model across simulations is shown in Figure 7. The model exhibited a decrease in looking time across trials (A), which happens as the model more frequently looks and looks away from the stimulus (B) and look durations become shorter (C). These changes in looking dynamics across trials are consistent with the empirical observation that infants exhibit shorter look durations across trials (Cohen, 1973; see also Clearfield & Fisher, 2009; Ruff, 1975).

Looking time to novel stimuli following the habituation phase is most often the behavioral measure of interest in studies using looking to measure infants’ developing perceptual and cognitive abilities. 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. When a novel stimulus excites neurons that are relatively uninhibited in PF, a robust peak emerges in PF and this field provides strong excitatory input to the fixation system that maintains fixation. Looking time increases, and the model, like infants, is said to dishabituate—the model discriminates between the habituation and novel stimulus.

To illustrate the mechanisms underlying discrimination in the model, I tested the model with a similar stimulus (close test) and a dissimilar stimulus (far test). The looking behavior of the old infant model to the close and far tests is shown in Figure 7A. As can be seen, the old infant model exhibits an increase in looking to the close test and relatively higher levels of looking to the far test. Figure 7D-E shows the state of PF and WM when the old infant model is looking at the close test (D) and far test (E). When the model looks at the far test stimulus, the stimulus excites relatively uninhibited neurons in PF. A robust peak forms in PF, which provides strong excitatory input to the fixation system and supports continued looking. When the model looks at the close test stimulus, support for fixation from PF arises from two sources. First, the strong lateral inhibition surrounding the peak in WM slows updating of WM for novel stimuli that excite those neurons. This prolongs encoding of the stimulus in PF, which, in turn, helps PF support longer looks to the close novel test stimulus. Second, strong excitatory connections within PF via the Hebbian layer sustain suprathreshold activation, which also helps PF support longer looks to the close test stimulus.

In summary, the DNF model establishes a link between looking and cognitive dynamics. As the model encodes a stimulus, looking time is high because strong activity in PF gives rise long look durations and few looks away. As the model forms a working and long-term memory for a stimulus, looking time is low because the inhibition in PF gives rise to short look durations and many looks away. The DNF model also specifies the mechanisms that underlie discrimination. The model dishabituates when a novel stimulus excites relatively uninhibited neurons in PF. Moreover, the level of dishabituation depends on the metric similarity of the novel item to the familiar item. These simulation results are consistent with empirical studies examining infants' looking to novel stimuli that vary in similarity from the habituation stimulus. For example, Brannon et al. (2006) found a linear relationship between dishabituation and the similarity of the novel stimulus to the familiar stimulus.

Developmental Change In Looking and Discrimination

Across the first year, infants habituate more quickly, exhibit shorter look durations, and are able to discriminate between similar familiar and novel stimuli. The old infant model captures this pattern of results. Here, I propose and implement a developmental hypothesis that captures the behavior of relatively younger infants. In particular, I generalize the Spatial Precision Hypothesis (SPH) from the domain of spatial cognitive development (Schutte & Spencer, 2009; Schutte et al., 2003; Simmering et al., 2008). The SPH posits that the strength of excitatory and inhibitory neural interactions increases with age. The SPH has captured developmental changes in children's performance in spatial recall tasks (Schutte & Spencer, in press), as well as position discrimination and the Piagetian A-not-B task (Simmering et al., 2008).

Here, I extend the SPH to capture developmental changes in infants' memory formation for visual features distributed along continuous dimensions. The SPH has not previously been used to capture developmental change in infant habituation. Note that I tested whether the neuro-developmental changes captured by the SPH produce both a decrease in processing speed and a reduction in discrimination. These developmental changes are widely viewed to arise from changes in the cognitive system. The SPH is consistent with this view, and below I test whether such changes are sufficient to capture developmental change.

Note that there are also pronounced changes in fixation dynamics that may influence changes in processing speed and discrimination. For example, shifting gaze involves moving the body, which infants become more proficient at during the first 3 months of life (Robertson, Bacher, & Huntington, 2001). Additionally, during the first 3 months of life, infants gain finer control over eye movements (for a review, see Johnson 2002). Early in development, infants' saccades are slow and they make several saccades when shifting gaze from one stimulus to another. Later in development, infants' saccades are faster and they make fewer saccades when shifting gaze. It is unknown whether these occulomotor changes and changes in motor control over the body are related, but they do occur during the same developmental period. Critically, improvements in motor control can shorten the duration with which infants look at a stimulus above and beyond changes in fixation dynamics that might be related to the processes of memory formation. Although manipulations of the fixation system in the DNF model could capture aspects of the developmental data reported here, I chose to ask a more constrained developmental question: is the SPH—a developmental hypothesis from another research domain—sufficient to capture developmental change in infant habituation.

The SPH was implemented on the old infant model by decreasing the strength of local excitatory connections in PF (c_{uu}) and WM (c_{ww}), as well as the strength of the inhibitory projection from Inhib to PF (c_{uv}) and Inhib to WM (c_{wv}) (see Schutte & Spencer, 2009). These parameter settings will be referred to as the "young infant model" (see Table 1).

The dynamics underlying the looking behavior of the young infant model are shown in Figure 8. As can be seen in panels A and B, the young infant model is comparable to the old infant model at the start of habituation. Notice, however, that the young infant model does not sustain a WM peak during the ISI of trial 4 (see lower panel in D) as the older model did. By trial 7, however, a WM peak has emerged and is beginning to suppress activity in PF. Figure 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 old infant model, I have reproduced Figure 6G in panel H). When the model begins each trial early in learning, the contribution of HL_{PF} to PF facilitates encoding (see positive activation in PF early in learning in the top panel of G). Late in learning, HL_{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 and establishes a relatively weak peak in PF. In Figure 8G, the transition from encoding to working memory formation can be seen in the 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.

Two differences between the young and old infant models are evident across Figure 8G-H. The first difference is that the contribution of HL_{PF} to PF is stronger early in habituation in the young infant model than the old infant model. This arises from differences in the time course of stable WM peak formation, that is, processing speed in the DNF model. The frequency of trials on which the young infant model formed a stable WM peak across simulations can be seen in Figure 9 (black bars, young infant model and gray bars, old infant model). As can be seen, the distribution of trials on which a stable WM peak was formed shifted later for the young infant model. These differences in encoding and working memory formation give rise to different patterns of looking during habituation. This is shown in Figure 10A-C (black lines; gray lines show the old infant model's performance for comparison). The young infant model exhibits a slower decline in looking time (A), a slower rise in the number of looks over learning (B), and a less steep decline in look durations relative to the old infant model (C). These developmental changes in looking behavior arise from the consequences of neural interaction strength. In particular, when interactions are weak, WM peaks emerge slowly, are smaller in amplitude, and they generate less inhibition early in habituation. This results in long bouts of looking to the habituation stimulus and a slower decline in looking. When interactions are stronger, by contrast, stimuli are encoded and working memories are established quickly. This generates a stable WM peak, more inhibition in PF, shorter bouts of looking to the habituation stimulus, and a relatively rapid decline in looking.

The second difference between the young and old infant model is that WM is less precise late in habituation for the young infant model than the old infant model. Strong neural interactions in the old model constrain the range of above-threshold neurons that participate in the excitatory interactions within a WM peak (Schutte and Spencer, 2009; for related ideas see Schutte et al., 2003). This is an emergent consequence of stronger cross-layer interactions between WM and Inhib. Strong excitation in WM produces strong activation in Inhib, which, in turn, projects strong inhibition back into WM. This interplay constrains which neurons rise above threshold in the excitatory WM field, effectively sharpening the peak in WM and creating strong lateral inhibition surrounding the peak (see lower panel of Figure 8H). Note that initial implementations of the SPH in the literature involved directly manipulating the width of excitatory and inhibitory connections to capture developmental changes in the precision of WM peaks (Schutte et al., 2003). More recently, Schutte and Spencer (2009) revealed that the *precision* of WM peaks can emerge from increases in the *strength* of neural interactions alone. I showed here that increases in the strength of neural interactions are also sufficient to give rise to emergent changes in the precision of WM peaks in an infant habituation context.

The differences in the strength of neural interactions and precision of WM peaks also lead to differences in discrimination between similar familiar and novel stimuli. The looking behavior of the young infant model to the close and far tests is shown in Figure 10A (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. Thus, the young infant model fails to discriminate the close test and only shows robust discrimination to a very different stimulus (the far test).

To illustrate the mechanisms underlying the model's looking behavior during the test phase, Figure 10F-G shows the state of PF and WM when the young infant model is looking at the close test (F) and far test (G). For comparison, Figure 10D-E reproduces the state of PF and WM for the old model on the close test (D) and far test (E). When the model looks at the close test, the stimulus excites neurons in PF that are strongly inhibited by the WM peak which is actively maintaining a representation of the habituation stimulus (see lower panel of F). Thus, the stimulus builds a relatively weak peak in PF and this field provides little support to the fixation system. Looking time does not exceed habituated levels and the model, like infants, is said to generalize. The mechanisms underlying dishabituation to the far test are comparable to the old infant model (compare Figure 10E & 10G).

In summary, the SPH generalizes from the domain of spatial cognitive development to infant looking and memory for features. To this point, the DNF model has overcome two limitations of existing models. First, the DNF model captures looking as an exploratory behavior in the same spirit as Robertson et al. (2004) while also capturing the stable way in which looking changes over the course of learning and development. Note, however, that I have yet to show that looking contributes *directly* to learning. Second, the DNF model captures developmental change in processing speed *and* discrimination within the same system. Furthermore, the SPH posits that these changes arise from the same mechanism. Below, I show that the DNF model overcomes the third limitation of existing models – looking and memory formation can involve non-linear transitions. I also show that looking contributes directly to learning.

Non-Linearities In Looking and Memory Dynamics

The looking behavior of the young and old infant models shown in Figure 10A-C and the activation profile of the young and old infant models shown in Figure 8G-H highlight the stable dynamics of the DNF model across simulations. This stability, however, is embedded within simulation-to-simulation variation. It is within this variation that non-linear transitions in looking and memory formation can be observed, as well as the contribution of looking to learning.

Figure 11 shows sample simulations of the young (A-C) and old (D-F) infant models for three indices of performance during habituation. Each simulation generally exhibits a decrease in looking time, an increase in number of looks, and a decrease in look duration across trials. Simulations of the old infant model generally show faster and more consistent changes in these measures relative to the young infant model. Nevertheless, there is striking variability across the simulations at each age.

Importantly, all simulations were run with very same parameters. Simulation-to-simulation variation in looking emerges over the course of habituation. A central contributor to this variation across simulations is variance in the time course of stable WM peak formation. As shown in Figure 9, some simulations form a stable WM peak early and others quite late. This non-linear neural event in the model can produce non-linear changes in looking. This is illustrated in Figure 12, in which I anchored three indices of looking to the trial on which the model formed a stable WM peak. Figure 12A-C shows the looking behavior of the young infant model for simulations that formed a stable WM peak on trials 5 (green line) and 8 (gray line), that is, for fast processing and slow processing simulations, respectively. Simulations that formed a stable WM peak late exhibited low levels of looking, a high number of looks, and short look durations early in habituation. Simulations that formed a stable WM peak early, by 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 cognitive systems. Critically, these initial fluctuations cascade into meaningful changes in learning dynamics over trials.

Figure 12D-F shows the looking behavior of the old infant model for simulations that formed a stable WM peak on trials 2 (green line) and 5 (gray line). Simulations that formed a stable WM peak on trial 5 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, working memory formation, and long-term memory formation. By contrast, simulations that formed a stable WM peak on trial 2 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.

There are two notable qualities to the looking dynamics in Figure 12. First, there is a sharp decline in looking time, a sharp increase in the number of looks, and a sharp decrease in look duration once a stable WM peak emerges over learning. These non-linear changes are a behavioral signature of memory formation. Second, the looking dynamics for the young and old infant models are quite similar – faster processing simulations in both groups show more looking time, fewer looks, and longer look durations early in learning. Additionally, the looking dynamics of fast processing simulations of the young infant model resemble the looking dynamics of slow processing simulations of the old infant model. This is particularly salient for the looking time and look duration measures.

In summary, the DNF model is able to capture non-linear changes in memory formation that, in turn, impact looking. The DNF model, then, does not assume, like other models do, that memory formation is a gradual, continuous process. Rather, the DNF model has aspects of linear *and* non-linear changes in memory formation: Hebbian learning accumulates gradually through time, while stable WM peaks emerge as a non-linear neural event that also impacts looking. Moreover, simulation-to-simulation variation in looking and memory formation emerged via stochastic fluctuations in the fixation and neural systems. Typically, individual differences in looking are described as reflecting stable characteristics of the infant. Indeed, there is good evidence that individuals exhibit similar patterns of looking across ages (e.g., Colombo, Mitchell, O'Brien, & Horowitz, 1987). However, simulations of the DNF model show that a single parameter setting can produce patterns of looking and learning within a range. This raises the question of whether stochastic fluctuations in looking also influence how looking and learning unfold over time for an individual infant.

Is the Spatial Precision Hypothesis Required to Capture Developmental Change?

In this chapter, I generalized the SPH from the domain of spatial cognitive development to infant habituation. Remarkably, the very same implementation of the hypothesis (i.e., manipulating the same parameters) that captured changes in children's performance in a spatial memory task (Schutte & Spencer, 2009) also captured a shift in habituation and discrimination during infancy. It is unclear, however, whether the SPH must be implemented in precisely the manner used here. To probe this, I examined whether the four parameters manipulated to implement the SPH must be changed together to capture developmental change in both habituation and discrimination. I did this in two steps. First, I performed a linear interpolation between the young and old infant models for each parameter of the SPH (c_{uu}, $c_{ww,}$ c_{uv}, c_{wv}). In particular, I divided the difference between the young and old infant model parameters into four proportional steps (+.25, +.5, +.75, +1), where 0 equals the parameter value for the young infant model and 1 equals the parameter value for the old infant model. Then, I conducted eight sets of simulations. In the first four, I manipulated each SPH parameter independently to probe its influence. In simulation sets 5 and 6, I manipulated SPH parameters together based on their type of connection, excitatory or inhibitory. In simulation sets 7 and 8, I manipulated SPH parameters based on the sub-system they govern, that is, PF or WM. Finally, I explored a final type of developmental change that should directly influence speed of processing—changing the build timescale of the Hebbian layers.

Independent parameter changes. Figure 13 (A-D) shows the looking time results during habituation and test for four sets of simulations in which I manipulated each SPH parameter independently of the other three. For reference, I also included looking time for the young infant model (black open circles) and old infant model (gray closed circles). Increasing self-excitation in PF alone ($c_{uu,}$ A) had little or no impact on habituation or discrimination, although the model did respond somewhat more robustly to the far test as strength increased. Increasing self-excitation in WM alone ($c_{ww,}$ B), by contrast, had a strong effect on habituation and discrimination. When increased by +.25

(blue squares), the model habituated more quickly than the old infant model, but showed no dishhabituation to the close test. The model did dishabituate to the far test. When increased by +.5 (red pluses), +.75 (green triangles), and +1 (cyan stars), the model habituated on the first trial and did not dishabituate to the close or far test. This occurs because WM is so robust that it suppresses encoding of both items. Thus, changes in WM alone led to faster speed of processing, but not enhanced discrimination.

Increasing the strength of the inhibitory connection from Inhib to PF alone ($c_{uv,}$ C) had little or no impact on habituation or discrimination. However, increasing the strength of the inhibitory connection from Inhib to WM alone ($c_{uv,}$ D) had a dramatic effect on habituation and dishabituation. As the strength of this connection increased, the model began to exhibit an increase in looking across trials and high levels of looking to the close and far tests. This occurred because inhibition effectively suppressed the model's ability to form a WM for the stimulus.

These simulation results show that changes in a single SPH parameter independent of the others does not capture developmental change in both habituation and discrimination. Thus, in the next section, I probe whether correlated parameter changes grouped by connection type – excitatory and inhibitory – might be an effective way to reproduce developmental change.

Connection-type parameter changes. System level changes in excitatory or inhibitory connections may be sufficient to capture developmental change in both habituation and discrimination. For example, increasing the strength of the connection from Inhib to PF (c_{uv}) *and* from Inhib to WM (c_{uw}) together might give rise to strong suppression of encoding and, thus, faster habituation. Similarly, stronger suppression of activity around remembered items in WM might slow updating for similar items and produce finer-grained novelty discrimination. Reversely, stronger self-excitation in PF (c_{uu}) and WM (c_{ww}) might give rise to faster WM formation and faster habituation. Stronger self-excitation in WM might also create more localized WM peaks and impact discrimination.

Figure 13E shows simulation results from increasing the strength of self-excitation in PF (c_{uu}) and WM together (c_{ww}). As the strength of self-excitation increased slightly (i.e., +.25), the model habituated quickly, but only dishabituated to the far test (see blue squares). As the excitatory strength increased, the model habituated on the first trial. It also showed no evidence of dishabituation to the close or far test because WM is so robust that it suppresses encoding of both items. Figure 13F shows simulation results from increasing the strength of inhibition from Inhib to PF (c_{uv}) and Inhib to WM (c_{wv}). As the strength increased, the model showed no evidence of habituation or dishabituation: with inhibition so strong, the model was unable to form WM peaks.

These results show that changes in the strength of SPH parameters based on the connection type does not capture developmental change in habituation and discrimination. This highlights an important property of the SPH that has emerged in the different studies probing this hypothesis: effective developmental change requires balanced changes in excitation and inhibition. This suggests a final type of parameter change to probe: localized parametric changes in PF *versus* WM, that is, to manipulate parameters that govern encoding independently from parameters that govern working memory.

Subsystem parameter changes. Changes in the strength of SPH parameters that influence encoding and the parameters that influence working memory might better capture developmental change than the manipulations above. Increasing the strength of self-excitation in PF (c_{uu}) and inhibition from Inhib to PF (c_{uv}) might lead to faster encoding and, thus, faster working memory formation. In addition, strong self-excitation in PF might enable the DNF model to robustly respond to the close test. By contrast, increasing the strength of self-excitation in WM (c_{ww}) and inhibition from Inhib to WM (c_{wv}) might lead to faster working memory formation and faster habituation. Strong reciprocal interactions between WM and Inhib might also give rise to sharper localized peaks like those that enable the old infant model to discriminate between the habituation and close test stimulus.

Figure 13G shows simulation results from increasing the strength of self-excitation in PF (c_{uu}) and inhibition from Inhib to PF (c_{uv}). These parameter changes had little effect on habituation or dishabituation. By contrast, Figure 13H shows the influence of WM manipulations. Increasing the strength of self-excitation in WM (c_{ww}) and inhibition from Inhib to WM (c_{wv}) produced a developmental profile that mirrors the developmental profile captured by the full SPH.

These results suggest that the SPH, as implemented, is not required to capture developmental change in both habituation and discrimination. To capture these changes, only the strength of reciprocal interactions between WM and Inhib must change. Importantly, it is unclear whether changes in these interactions are sufficient to account for empirical results in other domains or contexts. For example, changes in self-excitation in PF are critical for capturing developmental change in spatial recall (Schutte & Spencer, 2009). Changes in self-excitation in PF are also critical for capturing developmental change in infants' familiarity preferences between 6 and 8 weeks of age - a period in which familiarity preferences become increasingly more robust (Perone & Spencer, 2010; Wetherford & Cohen, 1972). I return to this issue in Chapter 5.

Hebbian Learning Rate. A remaining question is whether non-SPH parameter changes can capture developmental change in both habituation and discrimination equally well. I have shown that these developmental changes emerge from changes in neural dynamics. Perhaps a more intuitive approach, however, is to manipulate the speed at which the system forms memories. Decreasing the time scale (τ_{build}) at which Hebbian traces accumulate, that is, faster accumulation might impact habituation and discrimination in the same way as the SPH. Specifically, fast accumulation of activity in HL_{WM} can lead to fast WM formation and habituation of looking. Fast accumulation of activity in HL_{PF} can lead to strong initial responses to novelty, including to the close test. To examine this possibility, I decreased τ_{build} from 10000 by 25% (7500), 50% (5000), 75% (2500), and 100% (1). The simulation results are shown in Figure 14. As τ_{build} decreased, the model habituated more quickly but it did not exhibit any increased ability to discriminate between the habituation and close stimulus.

Conclusions of Chapter 3

In this chapter, I developed a new theory of infant looking and memory that overcomes three limitations of existing models. First, the theory captures developmental change in processing speed and discrimination within the same architecture. No previous model has captured developmental change in both processing speed and discrimination within the same architecture, which in needed to probe whether these changes can arise from the same mechanism. The DNF model posits that these changes do arise from the same mechanism, which I will probe experimentally in Chapter 5.

Second, the DNF model captures non-linear changes in memory formation that, in turn, impact looking in a non-linear way. Memory formation in habituation tasks has long been assumed to be gradual process. Although gradual changes in memory almost certainly occur in habituation studies, infants' looking can change qualitatively from one trial to the next, which suggests memory also undergoes a non-linear transition over the course of learning (Roder et al., 2000). Importantly, the DNF model has elements of both–the accumulation of Hebbian learning in the DNF model is gradual, yet the formation of a stable WM peak is a non-linear neural event that dramatically affects looking.

The final innovation is that the DNF model captures looking as an active behavior, linking looking to cognition to create a dynamic exploratory system. As I suggested in Chapter 1, a theory that establishes a link between looking and cognitive dynamics can enrich our empirical understanding of infant behavior. In Chapter 4, I demonstrate this in four ways. First, I examine whether the DNF model can be generalized to a more common task context for studying looking dynamics and recognition performance – the Visual Paired Comparison (VPC) procedure. Second, I examine whether infants, like the DNF model, discriminate along a single, continuous metrically organized dimension. Third, I examine whether individual differences in looking are linked to differences in discrimination in the model and infants. Finally, I test a novel prediction of the DNF model: under task contexts requiring fine-grained discrimination, human infants will show a familiarity bias that arises from robust memory.

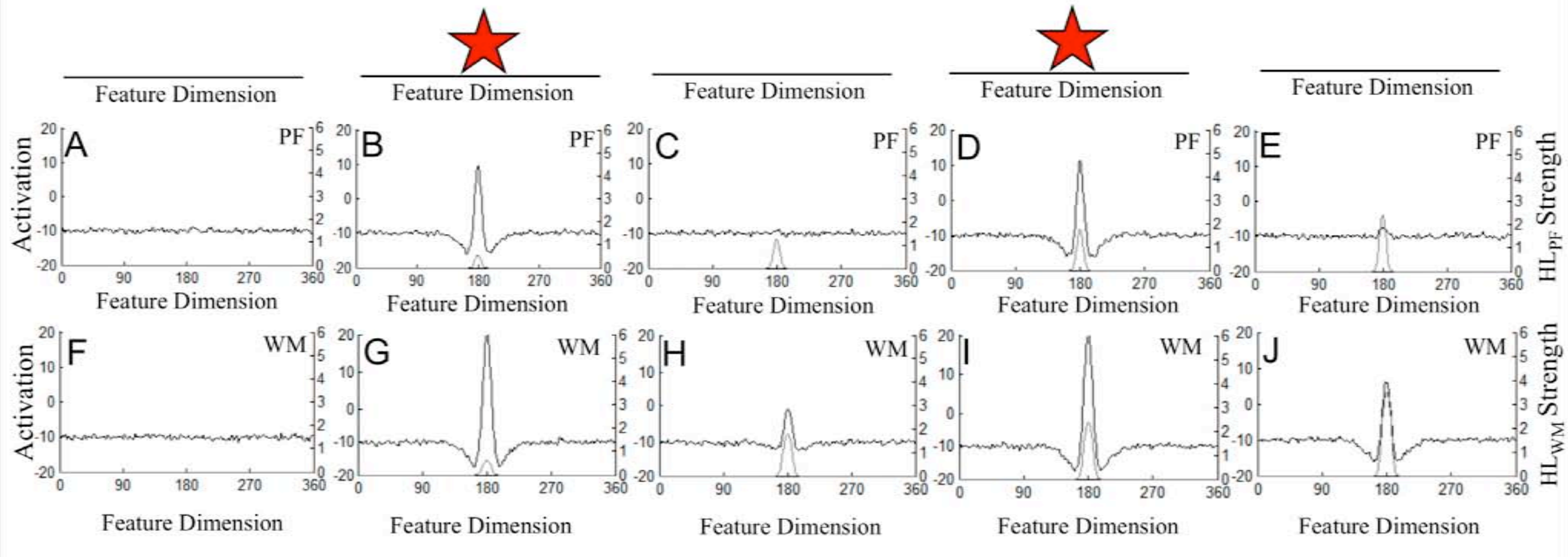


Figure 2. Self-Stabilized and Self-Sustaining States. Top row illustrates the self-stabilized state in PF. Initially, no stimulus is present and PF is in resting state (A). There is no contribution of HL_{PF} to PF (gray line, right y-axis). When a stimulus is present, interactions between PF and Inhib (not shown) create a self-stabilized peak and activation in HL_{PF} accumulates (B). When the stimulus is removed, PF returns to the resting state (C). When the stimulus is represented, the contribution of HL_{PF} to PF strengthens activation in PF (D). This 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. Initially, no stimulus is present and WM is in the resting state (F) and there is no contribution of HL_{WM} to WM. When a stimulus is present, interactions between WM and Inhib create a self-stabilized peak and activation in HL_{WM} accumulates (G). When the stimulus is removed, WM returns to the resting state (H). When the stimulus is represented, the contribution of HL_{WM} to WM strengthens activation in WM (I) and enables it to maintain a working memory (J).

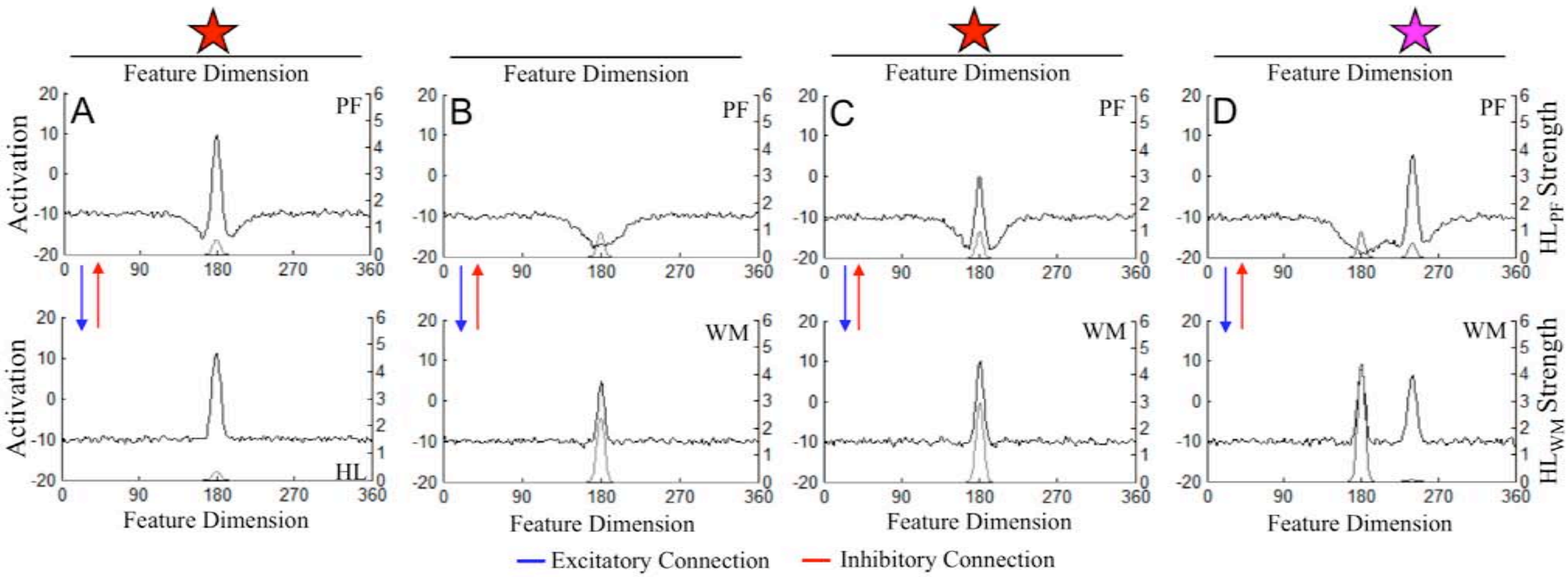


Figure 3. Recognition and Novelty Detection In 3-Layer+ Model. Illustrates how perceptual encoding in PF and working memory formation co-exist in DNF model. In this architecture, PF and WM share Inhib. When a stimulus is presented, activation in PF encodes the stimulus and feeds into WM (A). When the stimulus is removed, WM is tuned such that it is able to sustain a peak in the absence of input (B). Notice that inhibition in PF is strong, which arises from the contribution of WM to PF via Inhib (red 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.

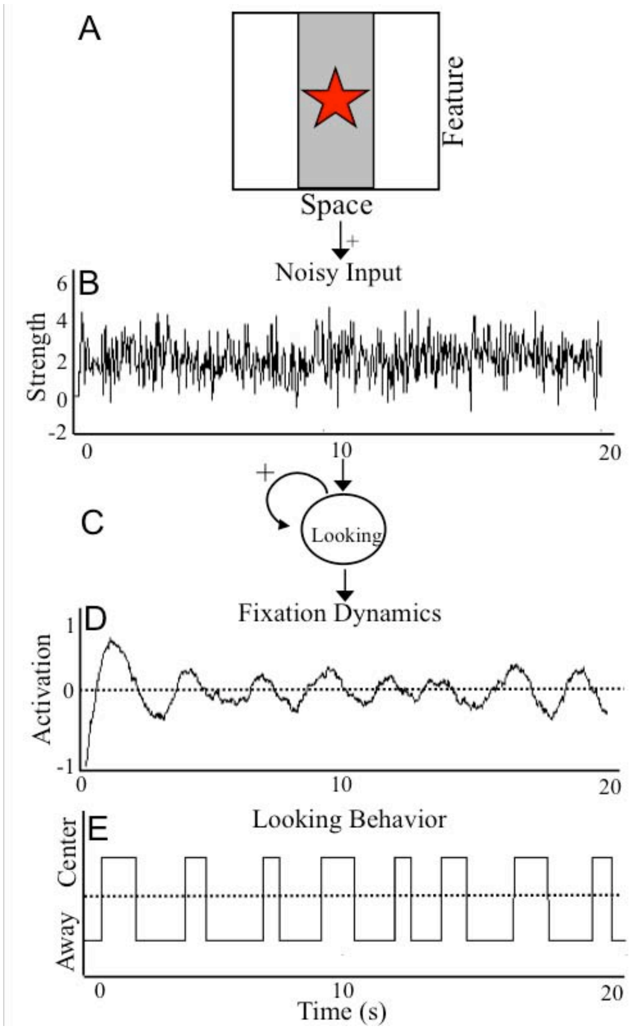


Figure 4. Fixation Dynamics. Architecture and behavior of the fixation system. The system looks and looks away from a single location at which a stimulus is present (A). When a stimulus is present at a center location, it presents noisy input to the fixation system (B). The combination of a self-excitatory connection within the fixation system and presence of noisy input (C) can bias the fixation system to enter and sustain suprathreshold 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).

Figure 5. Autonomous Looking and Learning. Illustrates the processes by which a dynamic exploratory system learns autonomously by looking. Panel A shows a single stimulus in the task space. Panel B shows the duration of looking and looking away from the stimulus across 200 s of exploration. Panel C shows the fixation dynamics that are directly translated into looking and looking away. Early in learning, the model exhibits few looks of long duration. Late in learning, the model exhibits many looks of short duration. This pattern of looking arises from the model encoding the stimulus early (D-E), which supports looking, and the emergence of a stable working memory peak late (F-H), which suppresses encoding and releases fixation.

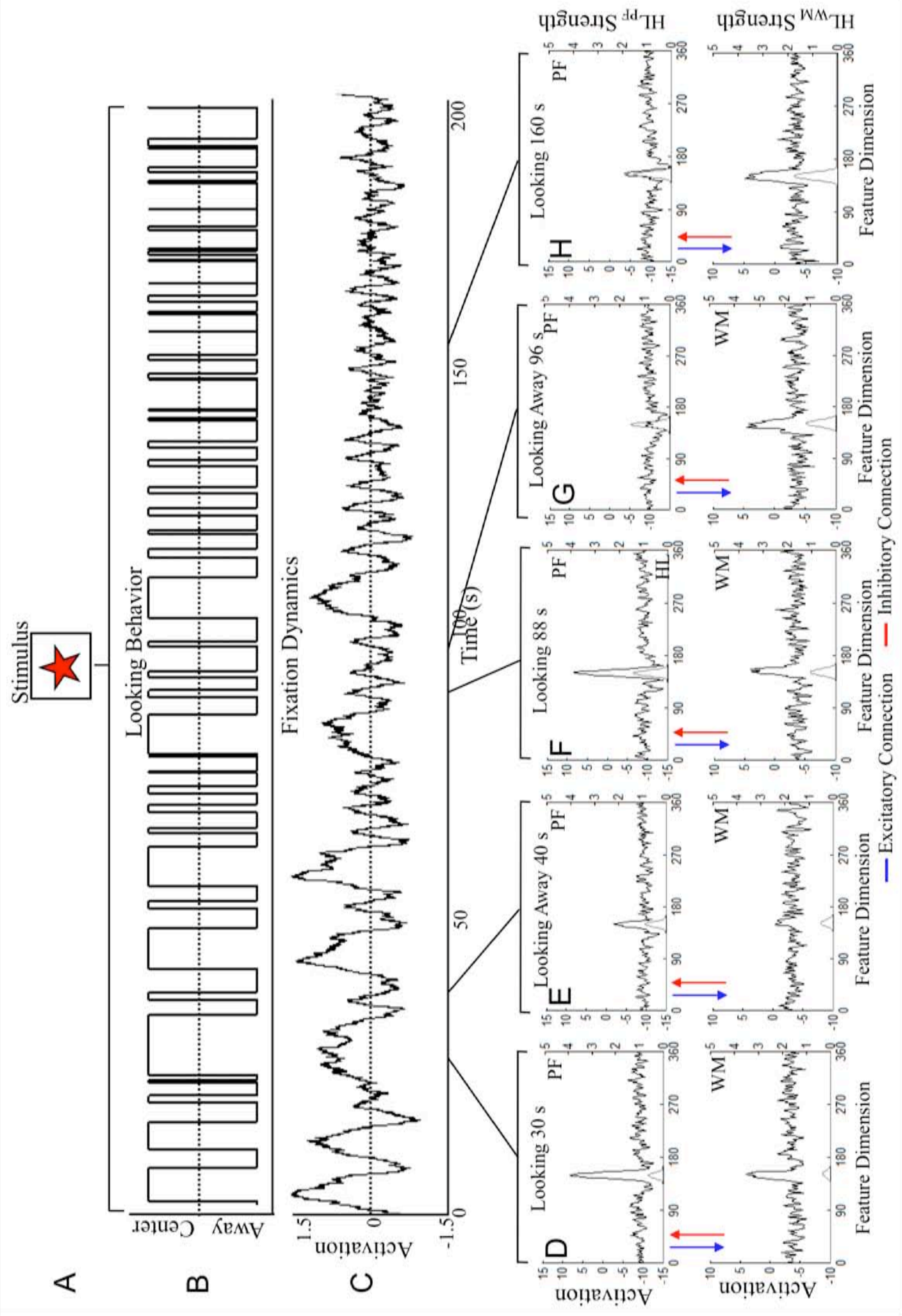

A
Stimulus
B
Looking Behavior
Center
Away
C
Fixation Dynamics
Activation
1.5
0
-1.5
0
50
100
150
200
Time (s)
D
Looking 30 s
E
Looking Away 40 s
F
Looking 88 s
G
Looking Away 96 s
H
Looking 160 s
PF
WM
HL
Activation
HL_PF Strength
HL_WM Strength
Feature Dimension
0
90
180
270
360
Excitatory Connection
Inhibitory Connection

Table 1. Model Parameters For Single Presentation Task

PF(u)			WM(w)			Inhib(v)			Fixation(f)		Time Scales (τ)		Hebbian Learning (hl)	
	Young	Old		Young	Old		Young	Old	All Ages		All Ages		All Ages	
h_u	-10.00	-	h_w	-3.50	-	h_v	-10.00	-	c_{ff}	1.20	τ_{excite}	80	c_{hl}	0.70
c_{uu}	**0.6930**	**0.7910**	c_{ww}	**0.7712**	**1.2323**	c_{uv}	**0.2385**	**0.2646**	c_{fu}	0.15	τ_{inhib}	10	σ_{uhl}	3.00
σ_{uu}	3.00	-	σ_{ww}	3.00	-	σ_{uv}	15.00	-	c_{uf}	1.00	τ_{build}	10000	c_{whl}	0.32
			c_{wu}	0.15	-	c_{vu}	0.80	-	h_{rest}	5.00	τ_{decay}	50000	σ_{whl}	3.00
			σ_{wu}	5.00	-	σ_{vu}	5.00	-	h_{down}	2.50				
						c_{wv}	**0.0225**	**0.1360**						
						σ_{wv}	15.00	-						
						c_{vw}	3.20	-						
						σ_{vw}	5.00	-						

Figure 6. Perceptual and Memory Dynamics In Old Infant Model. Shows the state of PF and WM in the old infant model across the habituation phase. Early in learning, the model encodes begins to form a memory for the stimulus as it looks and looks away (A-D). Late in learning, the model establishes a stable working memory for the stimulus, which suppresses encoding and leads to looking away (E-F). Panel G shows the activation profile of the old infant model at the onset of each habituation trial. The activation profile is the average state of PF and WM across simulations.

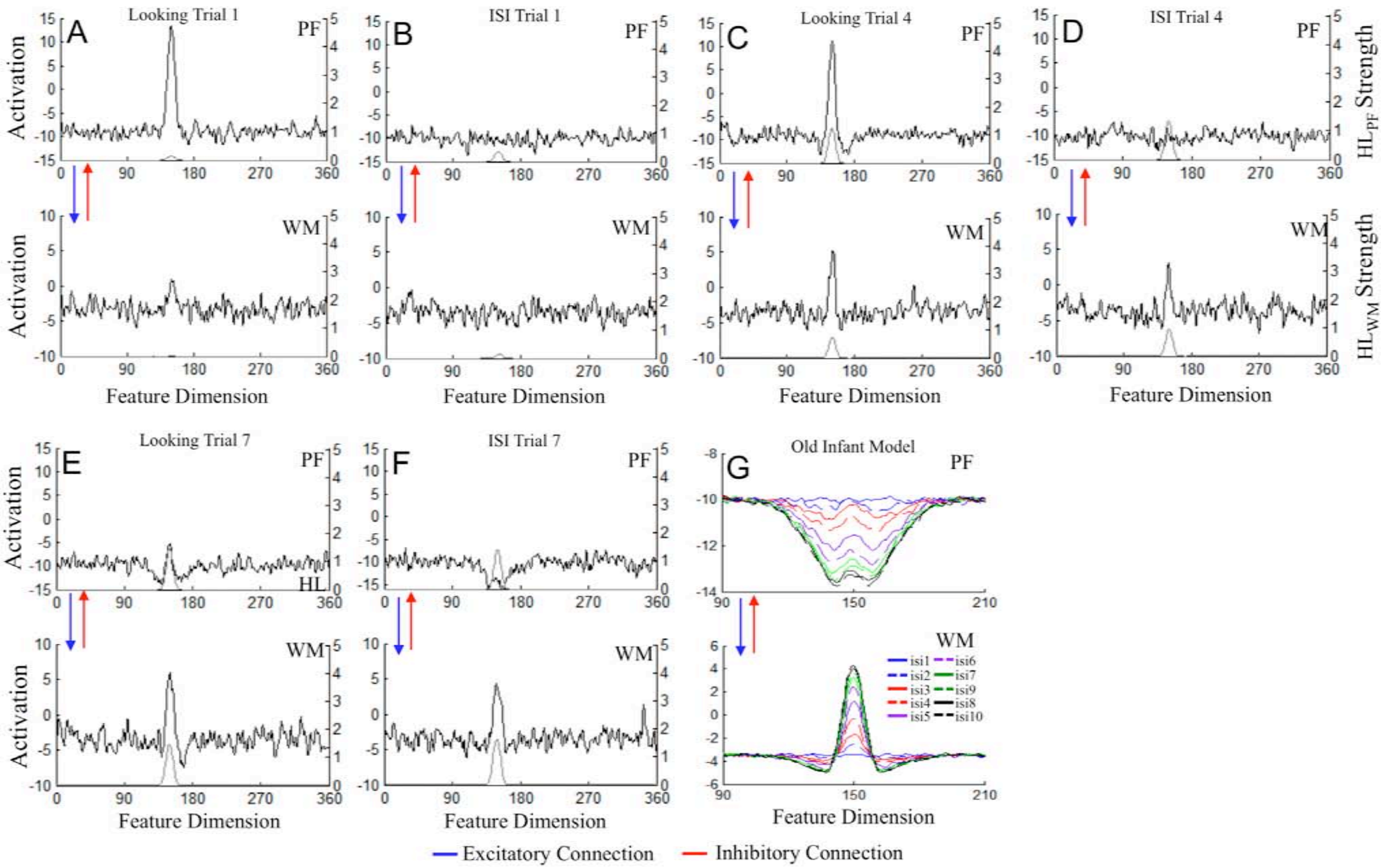

A
Looking Trial 1
B
ISI Trial 1
C
Looking Trial 4
D
ISI Trial 4
E
Looking Trial 7
F
ISI Trial 7
G
Old Infant Model
PF
WM
HL
Activation
HL_{PF} Strength
HL_{WM} Strength
Feature Dimension
15
10
5
0
-5
-10
-15
90
180
270
360
150
210
isi1
isi2
isi3
isi4
isi5
isi6
isi7
isi9
isi8
isi10
Excitatory Connection
Inhibitory Connection

Figure 7. Looking Behavior, Generalization, and Discrimination In Old Infant Model. Shows looking behavior of the old infant model during the habituation and test phases averaged across simulations (A-C). The old infant model shows a relatively rapid decline in looking across trials (A), an incline in number of looks across trials (B), and increasingly short look duration across trials (C). The old infant model exhibits an increase in looking time to both the close and far tests. Panels D-E illustrate the mechanisms of dishabituation to the close (D) and far (E) tests. 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. When the model looks at the close test, the stimulus excites inhibited neurons. However, strong excitation in PF (see top panel in D) and strong lateral inhibition in WM (see bottom panel in D) slows updating and helps support fixation.

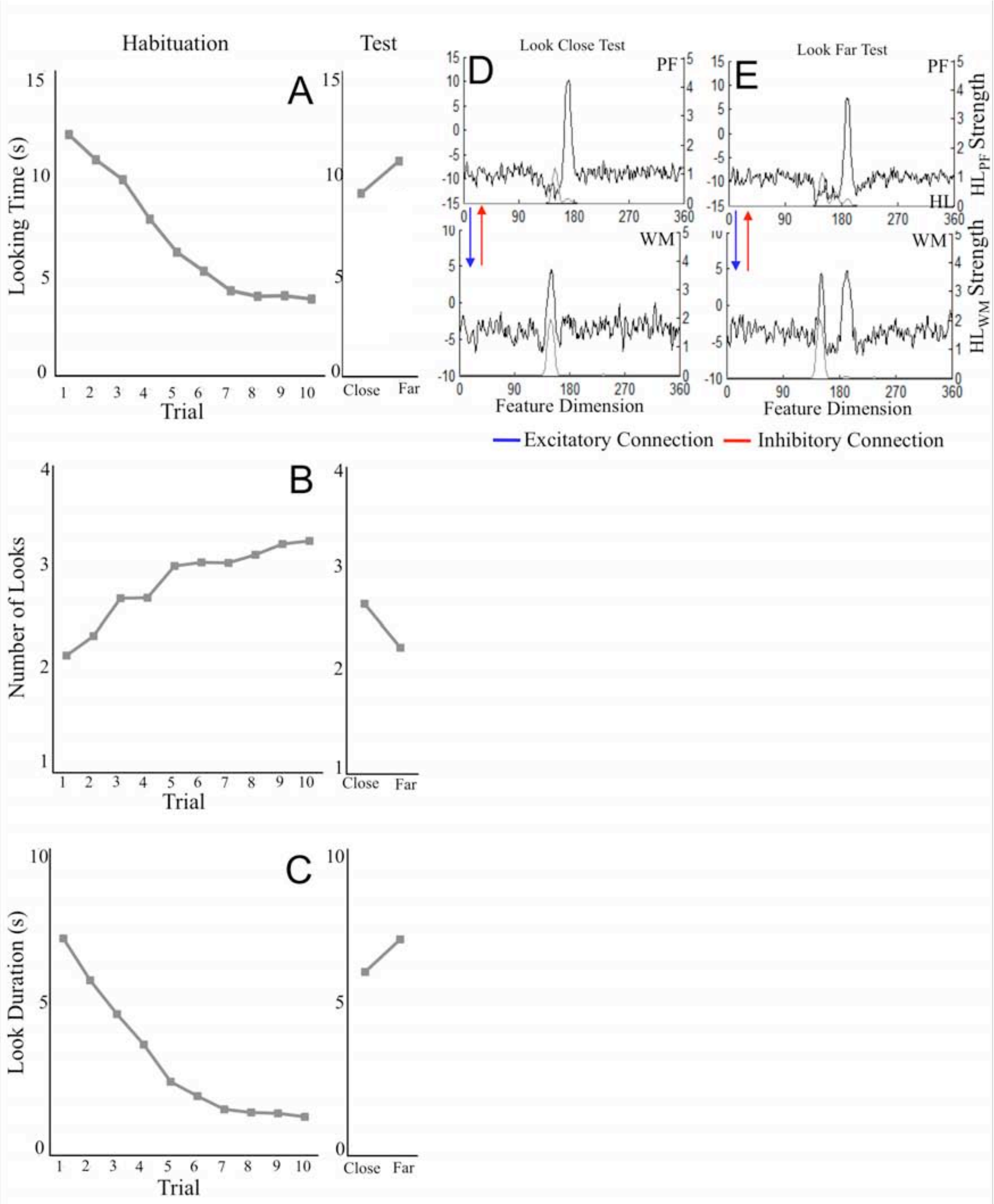
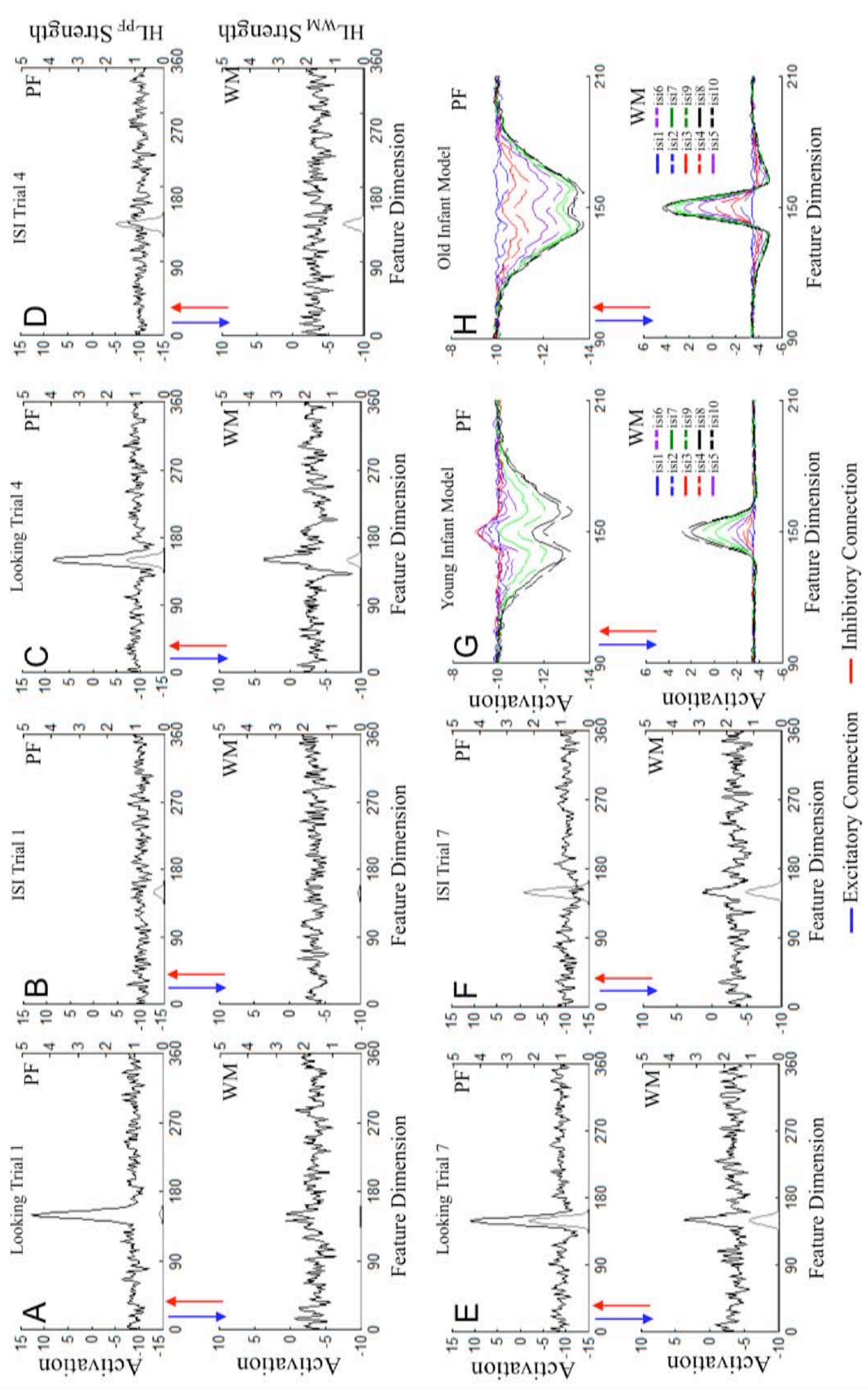

Habituation
Test
A
B
C
D
E
Looking Time (s)
Number of Looks
Look Duration (s)
Trial
Close
Far
Look Close Test
Look Far Test
PF
WM
HL
HL$_{PF}$ Strength
HL$_{WM}$ Strength
Feature Dimension
Excitatory Connection
Inhibitory Connection

Figure 8. Perceptual and Memory Dynamics In Young Infant Model. Shows the state of PF and WM in the young infant model across the habituation phase. As in the old infant model, early in learning the model encodes and begins to form a memory for the stimulus (A-D). Late in learning, the model establishes a stable working memory for the stimulus, which suppresses encoding and leads to looking away (E-F). Panel G shows the activation profile of the young infant model at the onset of each habituation trial. For comparison, panel H shows the activation profile of the old infant model.


A
Looking Trial 1
B
ISI Trial 1
C
Looking Trial 4
D
ISI Trial 4
E
Looking Trial 7
F
ISI Trial 7
G
Young Infant Model
H
Old Infant Model
PF
WM
Activation
Feature Dimension
HL_PF Strength
HL_WM Strength
0
90
180
270
360
150
210
isi1
isi2
isi3
isi4
isi5
isi6
isi7
isi8
isi9
isi10
Excitatory Connection
Inhibitory Connection

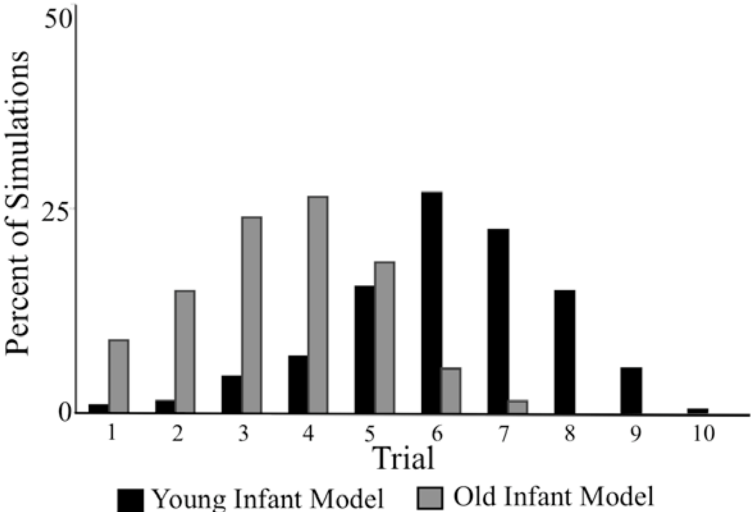


Figure 9. Distribution of Working Memory Formation Across Development. Shows the distribution of trials on which the young infant (black bars) and old infant (gray bars) model first formed a stable WM peak across simulations. The young infant model most frequently formed a WM peak on trials 5-8, whereas the old infant model tended to form a stable working memory on trials 2-5. Developmental change in processing speed within the DNF model arises from changes in the rate at which a stable WM peak arises. These differences in the rate at which the young infant and old infant models form a stable working memory are attributable to the SPH.

Figure 10. Looking Behavior, Generalization, and Discrimination In Young Infant Model. Shows looking behavior of the young (black lines) and old (gray lines) infant models during the habituation and test phases averaged across simulations (A-C). The young infant model is slower to exhibit a decline in looking (A), exhibits few 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. Panels F-G illustrate the mechanisms of generalization of looking (F) and dishabituation (G) in the young infant model. When the model looks at the close test, the stimulus excites strongly inhibited neurons in PF from the active maintenance of the stimulus in WM. 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. For comparison, Panels D-E show the dynamics of PF and WM for the old infant model at test, for comparison.

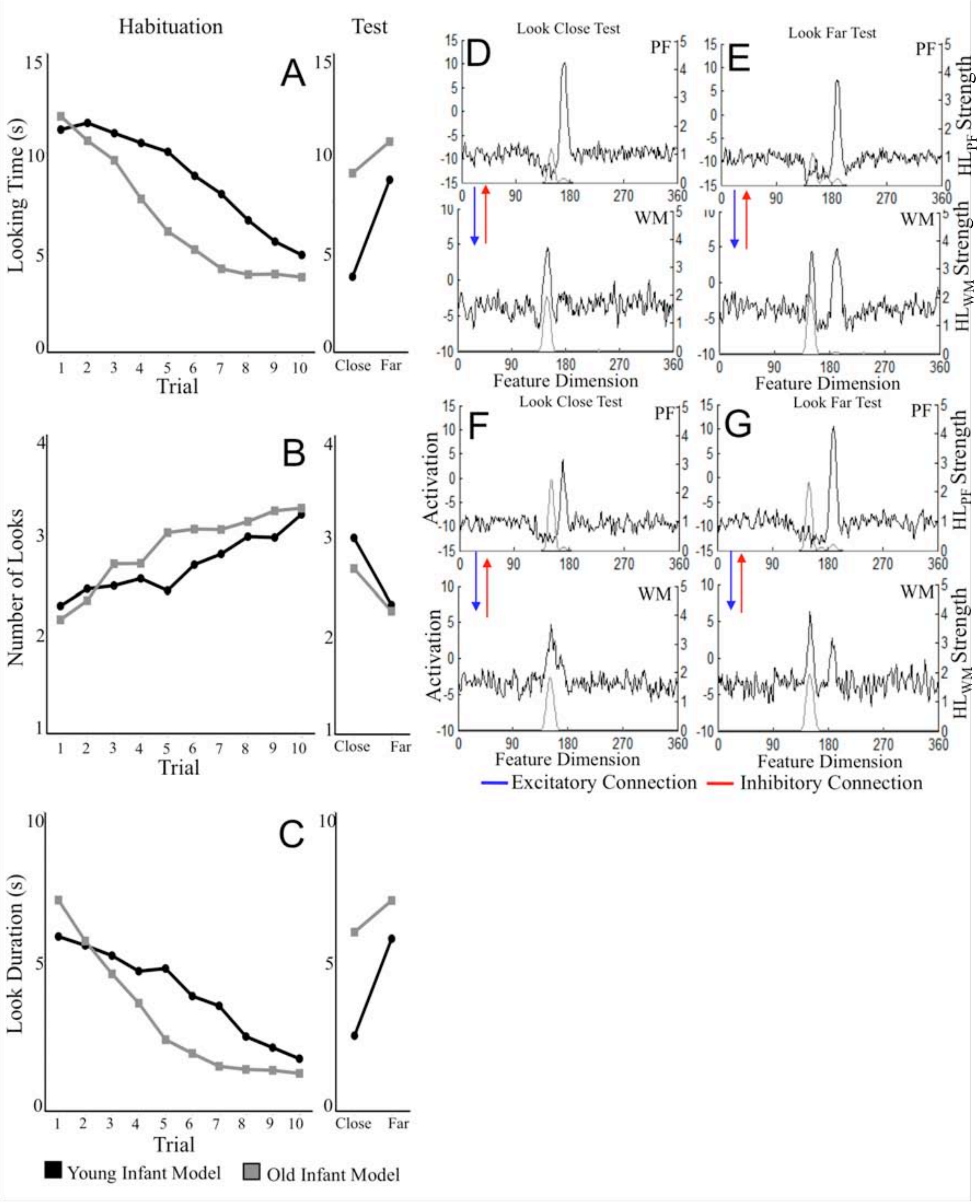

Habituation
Test
A
B
C
D
E
F
G
Looking Time (s)
Number of Looks
Look Duration (s)
Trial
Close
Far
Look Close Test
Look Far Test
PF
WM
HL_PF Strength
HL_WM Strength
Activation
Feature Dimension
Excitatory Connection
Inhibitory Connection
Young Infant Model
Old Infant Model

Figure 11. Simulation-to-Simulation Variation In Looking Dynamics. A sample of the looking time, number of looks, and look duration during the habituation and test phase from five simulations of the young infant model (A-C) and old infant model (D-F). 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.

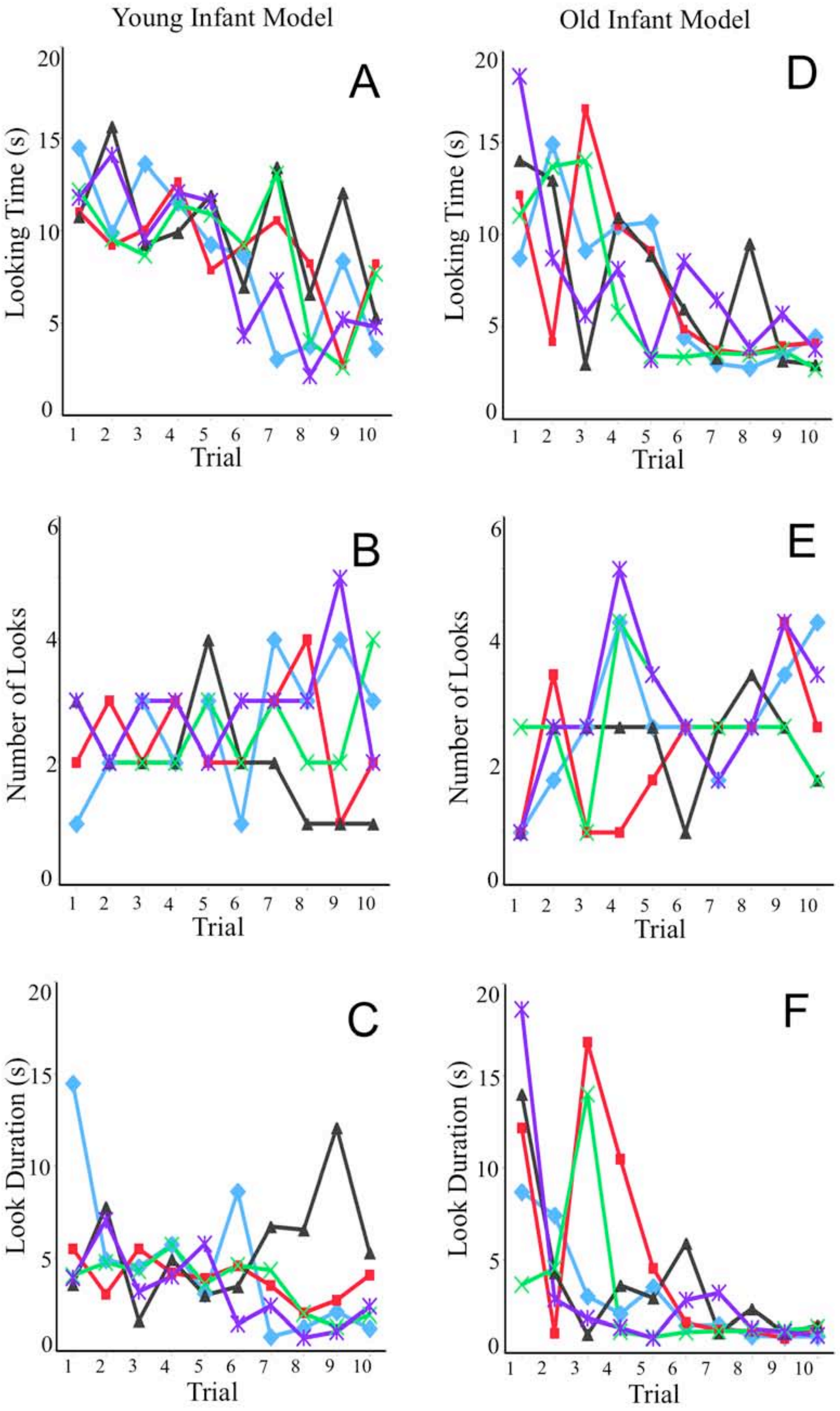

Young Infant Model
Old Infant Model
A
Looking Time (s)
0
5
10
15
20
Trial
1
2
3
4
5
6
7
8
9
10
D
B
Number of Looks
0
2
4
6
E
C
Look Duration (s)
F

Figure 12. Non-Linear Link Between Looking and Memory Dynamics. For the young infant model, looking time (A), number of looks (B), and look duration (C) is anchored to the trial on which a stable working memory was formed. Shows looking for simulations that formed a working memory early on trial 5 (green line) and late 8 (gray line). The same looking measures are shown for the old infant model for simulations that formed a working memory early on trial 2 (green line) and late trial 5 (gray line). For both models, more looking, fewer looks, and longer look durations early were associated with faster working memory formation. Once formed, working memory gave rise to sudden changes in looking including a dramatic decline in looking, increase in the number of looks, and decrease in look duration.

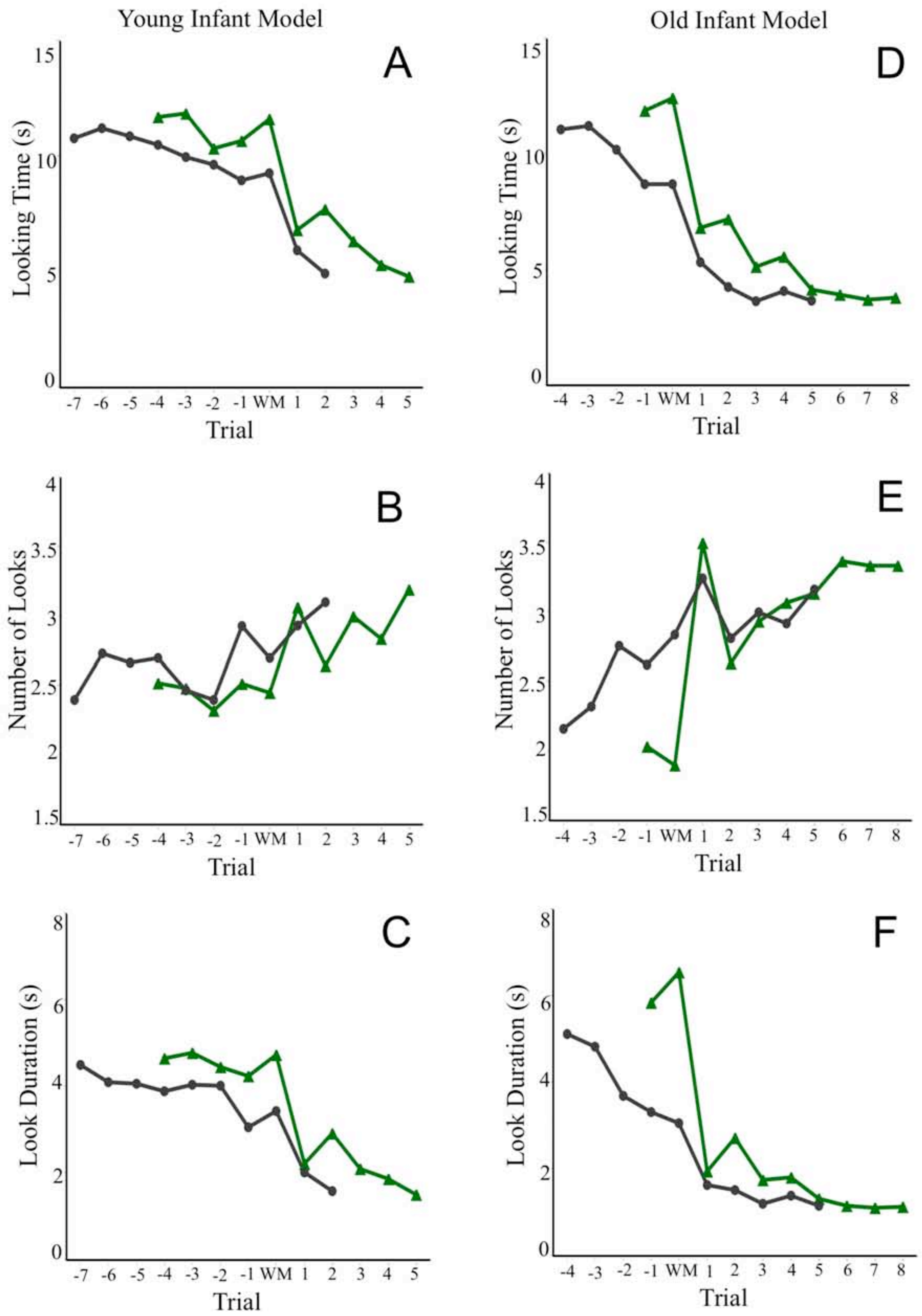
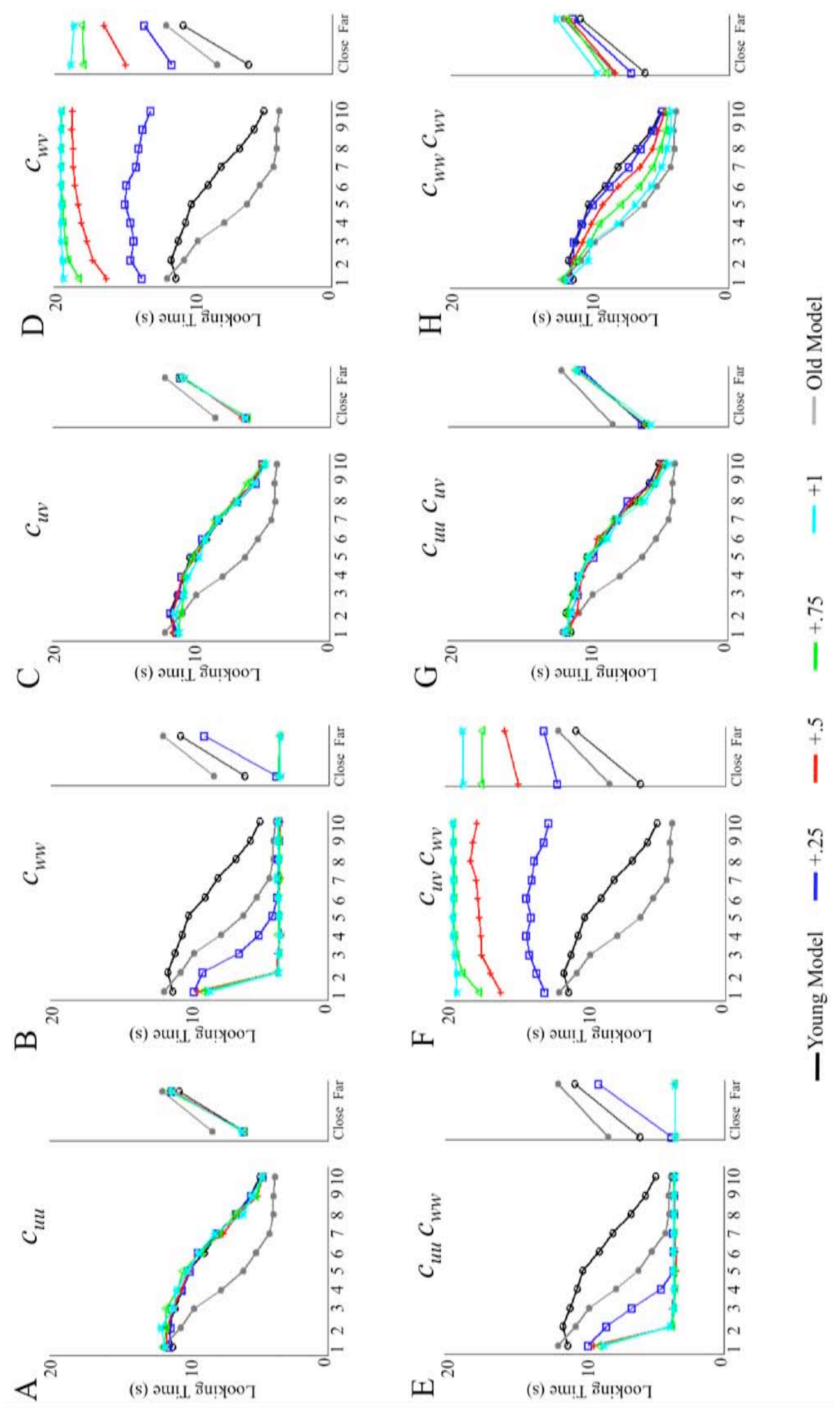

Young Infant Model
Old Infant Model
A
B
C
D
E
F
Looking Time (s)
Number of Looks
Look Duration (s)
Trial
0
5
10
15
1.5
2
2.5
3
3.5
4
0
2
4
6
8
-7 -6 -5 -4 -3 -2 -1 WM 1 2 3 4 5
-4 -3 -2 -1 WM 1 2 3 4 5 6 7 8

Figure 13. Testing the Spatial Precision Hypothesis. Results from simulations testing whether the spatial precision hypothesis parameters are required to capture developmental change in both looking and discrimination. Each simulation set manipulated one or more SPH parameters on a linear scale from the young infant setting for a given parameter to the old infant setting for that parameter in proportional steps of : +.25 (blue line), +.5 (red line), +.75 (green line), +1 (cyan line). The results for the young (gray line) and old (gray line) infant model parameter settings are shown for comparison. Panel A-D show single parameter changes. (A) increases in self-excitation within PF; (B) increases in self-excitation within working memory; (C) increases in inhibition from Inhib to PF; (D) increases in inhibition from Inhib to WM. Panesl E-F show parameter changes based on connection type. (E) increases in self-excitation within PF and WM; (F) increases in inhibition from Inhib to PF and to WM. Panels G-H show parameter changes based on “sub-system”, perceptual or memory. (G) increases in self-excitation in PF and inhibition from Inhib to PF; (H) increases in self-excitation in WM and inhibition from Inhib to WM.


A
c_{uu}
B
c_{ww}
C
c_{uv}
D
c_{wv}
E
$c_{uu}\,c_{ww}$
F
$c_{uv}\,c_{wv}$
G
$c_{uu}\,c_{uv}$
H
$c_{ww}\,c_{wv}$
Looking Time (s)
0
10
20
1 2 3 4 5 6 7 8 9 10
Close
Far
Young Model
+.25
+.5
+.75
+1
Old Model

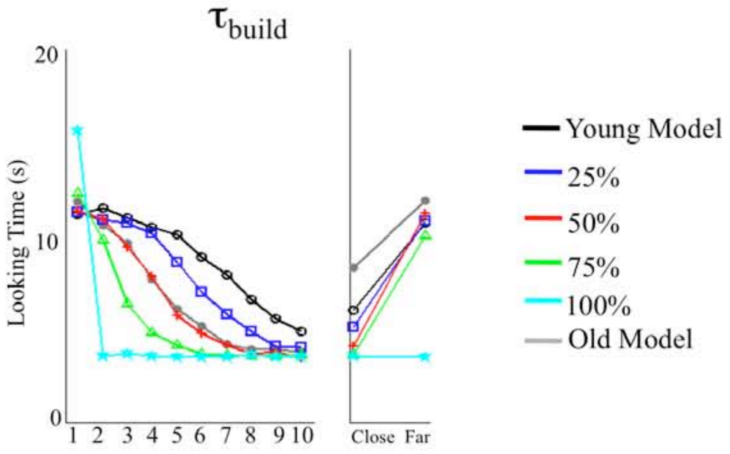


Figure 14. Testing Hebbian Learning Rate. Results from simulations testing whether the rate at which Hebbian learning occurs within PF and WM was sufficient to capture developmental change in both looking and discrimination. On the left is looking time during habituation. On the right side is looking to the close and far tests. The time scale by which HL accumulates was sped by 25% (blue line), 50% (red line), 75% (green line), and 100% or a value of 1 (cyan line). The looking of the young (gray line) and old (black line) models are shown for comparison.

CHAPTER 4

METRICALLY ORGANIZED STIMULUS REPRESENTATIONS IN INFANTS

In Chapter 3, I showed that the DNF model can capture developmental change in looking and discrimination within a single architecture in a single presentation habituation task. I also showed that change in these behaviors can arise from the same mechanism. One goal of this chapter is to test whether the DNF model can capture infants' performance in the Visual Paired Comparison (VPC) task, the task commonly used to probe changes in speed of processing over development. The VPC and single presentation tasks differ in at least two ways. The first and most obvious difference is that in the VPC, infants learn about one item across looks to identical items paired together, whereas in the single presentation task, infants learn about one item at a central location. In the VPC, then, infants look at a stimulus, disengage fixation, and switch gaze to look at the same stimulus at another location. This can lead to shorter average look durations than in single presentation tasks, which might impact memory formation (Oakes & Ribar, 2005).

Another difference between the two procedures is what constitutes evidence of recognition and discrimination at test. In a single presentation task, recognition and discrimination are inferred from two measures across separate trials. Recognition is inferred from a decline in looking to the familiar stimulus during the habituation phase, and discrimination is inferred when looking is renewed to elevated levels to a novel stimulus. In the VPC, recognition and discrimination are inferred from one measure on a single trial – the novelty score, a relative percentage of time spent looking to a novel stimulus relative to a familiar one. A reliable novelty score above chance (.5) is assumed to reflect recognition of the familiar stimulus and discriminative encoding of the novel stimulus.

The VPC yields a richer set of looking dynamics than single presentation tasks. For example, shift rate – the rate of switching gaze relative to time spent looking – can only be measured in the VPC. Previous studies have shown that individual differences in such measures are related to differences in memory formation (Kovack-Lesh, Horst, & Oakes, 2008; Rose et al., 2001). In addition, familiarity biases are more likely to be observed in the VPC than single presentation tasks (for an exception, see Whetherford & Cohen, 1973). For this reason, the VPC is typically used to probe how the strength of memory changes with increasing exposure to a stimulus (Fantz, 1964).

A second goal of this chapter is to probe the DNF model for novel predictions about infants' metric representations on the featural dimensions of color and shape. A fundamental assumption of DNFs is that neuronal interactions take place over continuous, metrically organized dimensions. This feature has enabled DNFs to capture various empirical findings from literatures as diverse as infant cognition (Schöner & Thelen, 2006), spatial cognition (Schutte & Spencer, 2009), and visual cognition (Johnson et al., 2009). For example, using the same DNF model presented in Chapter 3, Johnson et al. (2009) showed that the metric similarity between remembered and novel items influences discrimination performance. In particular, the model was presented with two similar colors and one color that was dissimilar to the other two. The memories for the two similar colors interacted in working memory via local excitatory / lateral inhibitory interactions, effectively sharpening the WM peaks. This produced weak and narrow inhibition in PF. The single dissimilar peak, by contrast, was associated with a broader peak, producing strong and broad inhibition in PF. The sharper peaks enabled the model to detect novelty for very similar items. Note that the use of continuous, metric dimensions also enabled Schöner and Thelen (2006) to capture a variety of experimental results from Baillergeon's (1987) drawbridge experiments, in which infants look at screens that rotate to various degrees.

Previous studies have shown that infants can discriminate between familiar and novel stimuli that differ on a single magnitude dimension (Brannon et al., 2006). Previous studies have also shown that infants can discriminate between familiar and novel stimuli that differ on multiple feature dimensions (e.g., a green cross from a green circle) (Cohen et al., 1971; see also Cornell & Strauss, 1973; Saayman, Ames, & Moffett, 1964; Welch, 1974). Importantly, infants exhibit different patterns of discrimination on different dimensions. On magnitude dimensions, infants exhibit a graded pattern of discrimination, that is, infants respond less to similar familiar and novel items and more to dissimilar familiar and novel items (e.g. Brannon et al., 2006). By contrast, infants exhibit categorical discrimination for hue (Bornstein, Kessen, & Weiskopf, 1976) and auditory dimensions such as voice onset time (Werker & Lalonde, 1988). Thus, not all dimension are equally discriminated, which presumably depends in complex ways on infants experience with various dimensions over time. It remains unknown, how infants discriminate among color and shape dimensions when these features are embedded within multi-dimensional objects. Here, I tested discrimination under two conditions – one condition in which familiar and novel items are metrically similar, and one condition in which familiar and novel items are metrically dissimilar.

Below, I situated the DNF model in the VPC task and show that it produces looking behaviors typically measured in the task including indices of processing speed such as shift rate, average look duration, and peak look, as well as the novelty score. After that, I probe a novel prediction in the DNF model. In particular, I show that robust memory and the metric similarity between familiar and novel items both influence whether the model exhibits a familiarity or novelty preference. I then test the prediction with infants that familiarity biases can emerge late in learning from robust memory, even in situations where infants have just shown a novelty preference. That is, the model predicts a novelty-to-familiarity shift. This pattern would violate all current models of infant habituation and visual recognition.

The theoretical and empirical research presented below will allow me to examine how looking and discrimination change over development in Chapter 5. In particular, this work establishes the theory-experiment link required to use the DNF as a tool for understanding how looking and cognitive dynamics are linked over development. Moreover, examining how discrimination along a continuous feature dimension changes over development requires first establishing that infants are capable of discriminating along such dimensions from a stimulus set with well-controlled metric properties.

A Generalized Dynamic Neural Field Architecture

Figure 15 shows the DNF model situated in the VPC. To generalize the model to capture performance in the VPC, I made two modifications to the 3-layer+ model. First, I expanded the fixation system to look among left and right locations at which task relevant stimuli appear, a center location where an attention-getting stimulus appears, and away locations at which no task relevant stimuli appear. Second, I added a second dimension along which the model encodes and remembers stimuli by duplicating the neural architecture. When the model looks at a blue circle, for instance, it encodes the color in one network and shape in another. This is important because the open empirical question addressed here is whether infants can discriminate a change along a single, continuous metrically organized dimension embedded within a multi-dimensional object. The updated equations are below.

The equations for the left and right nodes are identical. The equation for the left node is:

$$\begin{gathered}\tau_{excite}\dot{fl}(t) = -fl + h_{fl} + c_{ff}\Lambda_{fl}(fl) + c_b + c_s \\ -c_{ci}\Lambda_{fc}(fc) - c_{ci}\Lambda_{fr}(fr) - c_{ci}\Lambda_{fa}(fa) \\ +\Lambda_{fl}(fl)\int c_{fu}\Lambda_{uc}(uc(x',t))dx' \\ +\Lambda_{fl}(fl)\int c_{fu}\Lambda_{us}(us(x',t))dx'\end{gathered}$$

This equation is identical to equation 10 for the center node with two exceptions. First, the left node receives excitatory input from a color dimension, PF(*uc*), and a shape dimension, PF(*us*). As in the simulations of the single presentation task, the excitatory input from PF(*uc*) is the sum of above-threshold activation across all sites, *x,* at time, *t*, $\Lambda_{fl}(fl)\int c_{fu}\Lambda_{uc}(uc(x',t))dx'$, which is gated by the thresholded activation in the left node, $\Lambda_{fl}(fl)$. Similarly, the excitatory input from PF(*us*) is the sum of above-threshold activation across all sites, *x,* at time, *t*, $\Lambda_{fl}(fl)\int c_{fu}\Lambda_{us}(us(x',t))dx'$, which is also gated by the thresholded activation in the left node, $\Lambda_{fl}(fl)$. When the model fixates a blue circle, the blue color and circle shape are encoded in parallel and the activation associated with encoding each feature dimension is input into the fixation system simultaneously.

The second exception is that the left node receives inhibitory input from the current activity of the other nodes, for example, $c_{ci}\Lambda_{fr}(fr)$, which is the thresholded activation of the right node weighted by c_{ci}. When the right node pierces threshold, it has an inhibitory effect on the state of the left node. If activation in the left node is relatively weak, this can induce competition between the left and right nodes for fixation. This contributes to gaze switching.

As in single presentation tasks, infants are typically presented with an attention-getter at a center location prior to stimulus presentation at left and right locations. In the DNF model, the fixation system looks to away locations at which no task relevant stimuli appear at the onset of the experimental session and during each inter-stimulus interval. At the onset of each trial a strong, transient input is presented to the center node that quickly moves it from the "off" state to the "on" state, which, in turn, inhibits the away node and turns it from the "on" state to the "off" state. The presence of stimuli at the left and right locations then biases those nodes to compete for fixation.

The equation for the center node is:

$$\tau_{excite}\dot{fc}(t) = -fc + h_{fc} + c_{ff}\Lambda_{fc}(fc) + c_{ag} \\ - c_{ci}\Lambda_{fl}(fl) - c_{ci}\Lambda_{fr}(fr) - c_{ci}\Lambda_{fa}(fa)$$

This equation is identical to equation 10 except that it only is presented with an attention-getting input, c_{ag}. The center node receives no excitatory input from PF because attention-getters are removed from the display once fixated, minimizing the likelihood that the items are encoded.

The equation for the away node is:

$$\tau_{excite}\dot{fa}(t) = -fa + h_{fa} + c_{ff}\Lambda_{fa}(fa) + c_{sa} - c_{ci}\Lambda_{fl}(fl)$$

$$- c_{ci}\Lambda_{fr}(fr) - c_{ci}\Lambda_{fc}(fc)$$

This equation is identical to the center node except that it only has a static input, c_{sa}, that specifies the presence of task irrelevant stimuli during the entire experimental session.

The equation for PF (*uc*) is:

$$\begin{gathered}
\tau_{excite}\dot{uc}(x,t) = -uc(x,t) + h_u + S1_c(x,t)\Lambda(fl) + S2_c(x,t)\Lambda(fr) \\
+\int c_{uu}(x - x')\Lambda_{uc}(uc(x',t))dx' \\
-\int c_{uv}(x - x')\Lambda_{uv}(vc(x',t))dx' \\
+\int c_{uhl}(x,x')hl_{uc}(x,t)dx' \\
+c_{uf}\Lambda(fl) + c_{uf}\Lambda(fr) \\
+noise
\end{gathered}$$

This equation is identical to equation 1; however, there are multiple stimuli possible and each stimulus specifies values along the color and shape dimensions. As before, a given stimulus value is only input into PF when the location associated with the stimulus is fixated. This gating is achieved by weighting the stimulus by the thresholded activation of the fixation system, for example, weighting *S*1 by the thresholded activation of the left fixation node, $S1_c(x,t)\Lambda(fl)$. This sets *S*1 to 0 when the fixation system is not looking left, that is, when left node is below 0. The equation for PF(*u*c) is identical to PF(*u*s).

The equation for WM (*wc*) is:

$$\begin{gathered}
\tau_{excite}\dot{w}c(x,t) = -wc(x,t) + h_w + cS1_c(x,t)\Lambda(fl) + cS2_c(x,t)\Lambda(fr) \\
+\int c_{wu}(x - x')\Lambda_{wu}(uc(x',t)dx' \\
+\int c_{ww}(x - x')\Lambda_{ww}(wc(x',t)dx' \\
-\int c_{wv}(x - x')\Lambda_{wv}(vc(x',t)dx' \\
+\int c_{whl}(x,x')hl_{wc}(x,t)dx' \\
+noise
\end{gathered}$$

This equation is identical to equation 6 except that two stimulus values appearing at left and right locations can be input into WM, $S1_c(x,t)$ and $S1_s(x,t)$, as above. The equation for WM(*uc*) is identical to WM(*us*).

Figure 16 illustrates how the model captures performance in the VPC. The model was familiarized with pairs of identical items across 6 10 s trials. On a subsequent 20 s test trial, I tested the model's ability to discriminate between the familiar item and a metrically dissimilar item on one dimension by pairing the familiar item with a novel one. The left portion of the figure shows a sample of looking and associated states of PF and WM during the familiarization phase. The right portion of the figure shows a sample of looking and associated states of PF and WM during the test phase.

In Figure 16A, the left node (red line) is above threshold, suppressing activity of the right (blue line) and away (nodes). The stimulus at the left location (red star) is input into PF (B). Active neurons in PF excite similarly tuned neurons in WM. After approximately 1 s of looking, activation of the left node begins decrease in strength and approach threshold. This reduces the suppression of activity of the right and away nodes, which begin to rise toward threshold and compete for fixation. The away node wins, in this example. While looking away, activity in PF and WM subsides (C). The model happens to look right next, and an identical stimulus at the right location (red star) is input into PF.

Figure 16E shows the fixation system at test. Initially, the model is looking left at the familiar stimulus. Activation in PF is relatively weak due to the presence of strong activity in WM (F). This provides little support for fixation, which leads the model to exhibit a short look and switch gaze. The model looks right next, the location at which the novel stimulus is present. The novel stimulus is input into PF, which excites neurons uninhibited by the presence of strong activity in WM (see bottom panel G). The robust response of PF provides support for fixation, and the model shows a visual preference to look at the novel stimulus.

The expanded fixation system of the generalized DNF model enables it to produce the rich set of looking dynamics evident in the VPC. Figure 17A shows the novelty score, which I calculated across 200 simulations by dividing looking time to the novel item by total looking to the familiar and novel items. On average, the model exhibited a robust novelty preference. The model can also capture three well-known looking indices of processing speed - shift rate, look duration, and peak look. Figure 17B shows shift rate, which is the rate of switching gaze between left and right locations relative to the amount of time spent looking during the familiarization phase. In the model, gaze switching is influenced by noise (see Figure 16A) and strong memory (see Figure 16E), which reduce support for fixation (see Figure 16E). Figure 17C shows look duration, which is the average length of each look during the familiarization phase. Typically, shift rate and look duration are correlated. In the model, for example, shift rate increases as look duration decreases, r = -.76. Like gaze switching, look length is influenced by noise and memory formation. Finally, Figure 17D shows peak look, the longest look exhibited during the familiarization phase. Longer peak looks are likely to occur when memory is weak and encoding strong, but noise can also influence the duration of a look.

In summary, the DNF model can qualitatively capture performance in single presentation and VPC tasks. The model can produce a rich set of looking measures, including well-known looking indices of processing speed. Novelty scores in the model arise from relative differences in PF activity for familiar and novel items, which is influenced by the strength of WM for the familiar item. The fact that the DNF model generates both looking measures common in the literature and novelty preference scores suggests that this model could have a close tie to empirical work and be constrained by multiple measures of performance. Toward this end, I probe the model's ability to generate a novel empirical prediction in the next section. This would establish the utility of the model and its ability to connect looking and cognitive dynamics in human infants.

Memory-Induced Familiarity and Novelty Biases

It is widely accepted that familiarity and novelty bias are behavioral indices of cognitive processing underlying visual foraging, a ubiquitous exploratory behavior by which living organisms and artificial systems construct knowledge about foreign environments. Foraging has been studied extensively in living systems such as rabbits (Smith & Litvaitis, 2000), birds (Blough, 1984), squirrels (Duncan & Jenkins, 1998), and human infants (Robertson et al., 2004) and adults (Dodd, Van der Stigchel, & Hollingworth, 2009), as well as artificial robotic (Mobus & Fisher, 1999), neural (Perone & Spencer, 2010), and behavioral (Robertson et al., 2004) systems. Visual foraging is believed to reflect a process by which representations of items in the environment are formed. These representations, in turn, support recognition and novelty seeking.

Less clear, however, are the origins of familiarity seeking behaviors. Whether adults exhibit a familiarity or novelty bias depends on the task context (Dodd et al., 2009). When casually viewing a visual scene, for instance, adults frequently re-fixate familiar, remembered items. When searching for a particular item in a visual scene, however, adults more frequently fixate novel items. Whether adults exhibit a familiarity or novelty bias also depends on the stimulus context. For example, Park, Shimojo, and Shimojo (2010) presented participants with pairs of different items across a series of trials and asked them to indicate what item was preferable and the strength of their preference. One item remained the same across trials (familiar), and one item was changed on each trial (novel). For faces, adults exhibited an increasing familiarity preference across trials. For natural scenes, by contrast, adults promptly exhibited a novelty preference that remained saturated across trials. These findings show that, in adults, robust memory can lead to a familiarity bias.

Understanding the conditions under which familiarity and novelty biases arise is a particularly salient issue in the infant cognition literature. A robust empirical finding from this literature is the familiarity-to-novelty shift in which infants exhibit a bias to look at a familiar item relative to a novel one after brief exposure (or early in learning) and a bias to look at a novel item relative to a familiar one after prolonged exposure (or late in learning; Fantz, 1964; Roder et al., 2000; Rose et al., 1982). This shift has been the centerpiece of theories of infant habituation (Hunter & Ames, 1988), which posit that familiarity biases arise early in learning as infants initially encode and begin to form a memory for a stimulus, and novelty biases arise late in learning as a robust memory is formed that supports recognition of the familiar item. Like adults, however, whether infants exhibit a familiarity or novelty bias appears to depend on the task context. For example, Shinskey and Munakata (2005) presented infants with one object across a series of familiarization trials and allowed them to reach for it. Following familiarization, infants saw either the familiar object or a novel object hidden in the dark or visible in the light. Infants searched for the familiar item when hidden in the dark and searched for the novel item when visible in the light. These findings indicate that robust memory can induce a familiarity bias under demanding task conditions in which infants reach for objects. Here, I test whether robust memory induces a familiarity bias in a demanding discriminatory context.

Over the past several decades, neural network models have made a substantive contribution to our understanding of fundamental visual cognitive processes. Nevertheless, the origins of familiarity biases have largely eluded them. Only two models have provided possible mechanisms for familiarity biases (Schöner & Thelen, 2006; Sirois & Mareschal, 2004), and both posit that familiarity biases arise from weak memory and novelty biases arise from robust memory.

Simulations of the DNF model in a single presentation habituation task have shown that this model can capture familiarity biases early in learning due to initially weak memory for a stimulus (Perone & Spencer, 2010). Critically, however, *familiarity biases can also arise from robust memory when the model is asked to make a fine-grained discrimination late in learning*, that is, when the familiar and novel item are quite similar. Figure 18A-D illustrates this prediction. When the model looks at pairs of identical items across a familiarization phase (A), it encodes and forms a working memory for the item (see blue item). Across looks, the strength of the Hebbian contribution (see purple line, right y-axis) also increases, which boosts the neuronal response to the familiar item upon subsequent fixations.

Figure 18B-C shows how novelty biases arise when the familiar and novel item are dissimilar. In this example, the familiar and novel item are three equidistant metric steps (see pink circle in Figure 18B). When the model looks at the novel item, the stimulus excites neurons outside of the inhibitory trough in PF produced by strong activity in WM. Activation in PF is strong (red line), the stimulus is actively encoded, and looking time is high because the WM peak for the new stimulus is weak (see lower panel). When the model looks at the familiar item (C), however, a strong WM peak quickly emerges and inhibits the perceptual peak. Consequently, looking to the familiar stimulus is low. Across a series of looks, longer looking to the novel item and shorter looking to the familiar item yields a robust novelty preference.

Figure 18D shows a very different pattern of behavior that emerges, just seconds later, when the model is presented with the familiar item paired with a similar one that is novel by one metric step. When the model looks to the similar novel object, the stimulus excites neurons that fall within the inhibitory trough in PF. Consequently, activation in PF is quite weak (red line) and looking time is low. Critically, activation in PF is relatively stronger when the model looks to the familiar object because the baseline level in PF at the stimulated site is elevated due to the Hebbian contribution (see purple line in PF). This difference in PF biases the model to preferentially look to the familiar item over a similar novel one. Thus, the same memory representation that induces a novelty bias when familiar and novel items are dissimilar also induces a familiarity bias when familiar and novel items are similar. Note that robust memory leads to low levels of activation when the model looks to *both* the familiar and similar novel item, which, in turn, leads to low levels of total looking. This suggests that total looking time on this ‘one step’ test provides a good index of the strength of working memory. I probe this prediction quantitatively in the section that follows.

Model Simulations

Method

The simulations in Figure 18 show qualitatively how robust memory in the DNF model generates both a familiarity and novelty bias when the metric similarity between the familiar and novel items vary at test. I examined this prediction in quantitative detail by familiarizing the model with pairs of identical objects across 6 10 s trials. Recognition of the familiar item was tested across two 20 s test trials. One test was a *three step test*, in which the familiar item was paired with a dissimilar item that was novel by three equidistant metric steps on one dimension. The other test was a *one step test*, in which the familiar item was paired with a similar novel item that was novel by one metric step on the same dimension (see Figure 20). The order of the one step and three step tests was counterbalanced across 400 simulations. Looking time was calculated for each simulation for each test trial, and a novelty score was calculated by dividing looking to the novel object by total looking for each trial. Model parameters are presented in Table 2.

Results

The qualitative simulations in Figure 18 suggest that robust memory can induce a familiarity bias when familiar and novel items are similar, as on the one step test. But what constitutes a 'robust' memory? This is an important question in quantitative analysis of the model's performance given emergent individual differences in performance across simulations. This question is also important looking ahead to the goal of this quantitative analysis—predicting infants' performance.

In models, measuring robust memory is readily determined by the strength of WM on the test trial. In infants, however, one must rely on behavioral signatures of memory. Previous studies have shown that looking indices of processing speed such as shift rate, look duration, and peak look are associated with recognition performance (e.g., Rose et al., 2001; 2002), which suggests that these measures are a good index of robust memory formation. The qualitative analysis of the model in Figure 18 suggests that looking time on the one step test, that is, total looking across the familiar and novel item might be a good predictor as well.

To determine whether looking measures predict working memory strength as well as discrimination performance in the model, I conducted three sets of hierarchical regressions on the model's performance. All regression analyses in this thesis are presented in tables with the same structure (see Table 3 for an example). On the left, the step and predictor variables entered on each step are presented. The tables include summary statistics including R^2, change in R^2 across steps, change in the F statistic, and the probability value associated with the change in the F statistic. These summary statistics indicate the proportion of variance in the dependent measure accounted for and, in steps after the first step, whether that proportion was above and beyond the proportion accounted for in previous steps. On the right side of the table are the unstandardized beta weights (B). The sign of the beta weights indicate the direction of the relationship between a particular predictor variable and the dependent measure. The significance value of each predictor in the context of the other predictors entered on the step is also included, which indicates the relative strength of the predictors.

Predicting Working Memory Strength. Qualitative analysis of the DNF model suggests that strong WM can induce a familiarity bias on the one step test. Here I examined whether looking measures predict working memory strength entering the one step test. Results are shown in Table 3. In the first step, I entered the looking indices of processing speed (shift rate, look duration, and peak look) as predictors and the strength of WM as the dependent measure. Looking indices of processing speed did not account for a significant proportion of variance in the strength of WM entering the one step test trial. In the second step, I entered looking time on the one step test. Consistent with the qualitative analysis of the DNF model, looking on the one step test did account for a significant proportion of variance in the strength of working memory, change in R^2 =.04. Finally, on the last step I entered test order. Memory changes not only over the familiarization phase but also during test (Roder et al., 2000; Schöner & Thelen, 2006). Not surprisingly, then, order accounted for a significant proportion of variance in the strength WM going into the one step test trial. Interestingly, the slope of the beta weight was negative, indicating that the strength of working memory associated with the familiar stimulus actually decayed when the one step test was the second test trial. Similarly, Schöner and Thelen (2006) also found that memory for a familiar stimulus decayed during the first test trial while the model looked at a very different novel stimulus.

Looking on the one step test is a good predictor of working memory strength in the model, but is it also a good predictor of performance at test? To address this question, I again used hierarchical regression. In the first step, I entered shift rate, look duration, and peak look as predictors and novelty score on the one step test as the dependent measure. Results are shown in Table 4. These looking measures did not account for a significant proportion of variance in the novelty score on this test trial. In the second step, I entered total looking on the one step test as a predictor. This measure did account for a significant proportion of variance in the novelty score on this test trial, change in R^2 = .081. Note that the beta weight associated with looking on the one step test is positive, indicating that lower levels of looking are associated with familiarity biases. This is consistent with the qualitative analysis of the DNF model in Figure 18. In the last step, I asked whether order also contributed to the novelty score variability. Order made no additional contribution to novelty score variability. Order appears to be associated with WM strength but not performance on the one step test. This indicates that looking on the one step test is a good index of simulation-to-simulation differences in WM strength at test regardless of fluctuations in WM strength over test trials.

What about performance on the three step test? To examine the behavioral signatures that predict performance on the three step test in the model, I again used hierarchical regression. Results are shown in Table 5. Interestingly, shift rate, look duration, and peak look accounted for a significant proportion of variance in the novelty score on the three step test, R^2=.02, but looking on the one step test did not. This resembles similar analyses reported by Rose et al. (2001), who found that these measures were related to infants' novelty scores in a VPC task. The three step test is an easier discrimination than the one step test, which may better resemble the discrimination between familiar and novel items in Rose et al. where the items differed on multiple dimensions.

In summary, regression analyses indicate that low levels of total looking on the one step test are associated with strong WM entering the one step test as well as lower novelty scores (i.e., a familiarity bias). By contrast, these regression analyses suggest that the best predictor of performance on the three step test—the easier discrimination—are looking measures common in the infant literature. Because the central focus here is on the novel prediction of the model under conditions where a fine-grained discrimination is required, I parsed models into low and high looking groups based on a median split of total looking during the one step test. This generated quantitative predictions that I then tested with infants.

One Step Test. The performance of models with low looking on the one step test is shown in Figure 19A-C. The low looking group exhibited a familiarity preference on the one step test regardless of the order of test presentation (A). This familiarity bias arises from stronger activation in PF associated with the familiar item than the similar novel item, which provides more support to continue fixating the familiar item. This is illustrated in Figure 19B, which shows the average activation in PF while looking at the familiar item (black bar) versus the similar novel item (red bar).

The difference in activation in PF while looking at the familiar and similar novel item arises from the activation profile in PF created by its learning history and the state of WM at test. This is illustrated in Figure 19C which shows the state of PF while looking at the familiar item (black line) and similar novel item (red line) for low looking simulations. Activation was stronger while looking at the familiar item than the similar novel item. Strong activation while looking at the familiar item arises from increases in the Hebbian contribution to PF at sites previously stimulated by the familiar stimulus. Weak activation while looking at the similar novel item arises because there is no

Hebbian contribution for this item. In addition, it falls within the inhibitory trough created by the robust WM peak associated with the familiar item.

The high looking group performed quite differently. The performance of this group on the one step test is shown in Figure 19D-F. This group exhibited a null preference on the one step test regardless of its order of presentation (19D). This null preference arises from comparable levels of activation in PF associated with the familiar item and similar novel item (see Figure 19E), leading to comparable support to continue fixating each item. Figure 19F illustrates why this is the case: activation was moderately strong while looking at the familiar item (black line) and similar novel item (red line) because inhibition surrounding the familiar item was relatively weak. This weak inhibition arises from relatively weak activation in WM. In particular, the average strength of activation in WM entering the one step test was .94 for high looking simulations but 1.44 for low looking simulations. The null preference for the high looking group resembles concepts from Hunter and Ames' (1988) multi-factor model which posits that null preferences arise from the relatively equal strength of memory for the familiar item and the perceptual pull of the novel item.

Three Step Test. The regression analyses indicated that looking time on the one step test is only predictive of WM strength entering the one step test and novelty scores on the one step test. This makes some intuitive sense because the three step discrimination is likely to be quite easy for most simulations. Consequently, multiple factors might drive subtle differences in the magnitude of the novelty preference.

Indeed, as can be seen in Figure 19G and 19J, both the low looking and high looking groups exhibited a novelty preference on the three step test. For both groups, activation in PF was stronger while looking at the dissimilar novel item than while looking at the familiar item (compare red and black bars in 19H and 19K). This difference in PF activity arises from the state of PF (see 19I and 19L). Activation was stronger while looking at the dissimilar novel item (red line) for both groups because it excites neurons uninhibited by WM. This enables PF to respond robustly to the dissimilar novel item and support continued fixation.

In summary, simulation results for the low looking group show that robust memory can induce a familiarity bias in one stimulus context—the one step test—and a novelty bias in another—the three step test. This is consistent with data showing that familiarity biases can arise at test in demanding task contexts (Shinskey & Munakata, 2005). However, these simulations make a radical prediction—when the one step test is presented second, the model predicts a novelty-to-familiarity shift in the low looking group. This prediction runs counter to all other models of infant habituation and visual recognition which posit that familiarity biases arise early in learning due to weak memory. Below, I test these predictions with 10-month-old infants.

Experiment 1

In the DNF model, robust memory induces a familiarity bias in a low looking group when the familiar and novel item are similar and a novelty bias in both low and high looking groups when the familiar and novel item are dissimilar. I tested this prediction with 10-month-old infants in the same procedure as the model. I chose 10 months of age for three reasons. First, by at least this age infants can discriminate along a single continuous, metrically organized dimension embedded within multidimensional stimuli (Brannon et al., 2006; Brannon et al., 2007). Second, infants of this age are unlikely to exhibit familiarity biases from weak memory because they can quickly form working memories for visual stimuli (Ross-Sheehy et al., 2003) and require little exposure to a stimulus to recognize it (Rose et al., 2001). Last, I needed to establish an upper limit in discrimination performance with a relatively old infant age group to examine developmental change in discrimination with younger age groups in Chapter 5.

Method

Participants. Fifty 10-month-old infants participated in this study (*M*=304.72 days, *SD*=14.46 days; 28 boys, 22 girls). Five infants were excluded from the final analyses due to fussiness. Infants were predominantly from white middle class families, were full-term, and were healthy at time of test. Infants were given a small toy in appreciation for their participation.

Stimuli. Testing the prediction of the DNF model, and, more generally, investigating whether infants can discriminate along a single, continuous metrically organized feature dimension requires a stimulus set with well-controlled metric properties. Thus, I created a new stimulus set in which shape and color dimensions were varied continuously with well-controlled metric properties. The stimulus set is shown in Figure 20. Shape was defined by an aspect-ratio. Each metric step was defined by a proportional change in height and width, generating six equidistant metric steps with the total area of each stimulus held constant. Aspect-ratio is a relevant dimension along which categories can be discriminated. For example, Spivey (2007) found that adults parsed cups and bowls into categories based on aspect-ratio rather than width or height alone (see also Oden, 1981). Twelve equidistant colors were sampled from a 360°

continuous color space (CIE*Lab, 1976). The conjunction of one shape and one color constitute an object. The entire stimulus set consisted of 72 unique items.

Design and Procedure. Stimuli were presented on a 37” LCD monitor. Pairs of stimuli were centered equidistantly on the left and right portions of the monitor. Infants were tested in a dimly lit experimental room in which a black curtain hung from the ceiling to the floor to divide the room. The curtain had two openings in it. One opening revealed a 37” LCD monitor, and, directly below the monitor, one opening revealed a low-light TV camera lens used to view infants’ looking behavior.

Infants were tested in the same experimental design as the DNF model. Infants were familiarized with pairs of identical items across 6 10 s trials. The pair of identical items that each infant saw was randomly selected. Immediately following the familiarization phase, there were 2 20 s test trials (location of familiar and novel items were reversed after 10 s). One test trial was the one step test, in which the familiar item was paired with a similar item that was novel by one metric step on a single dimension (shape or color). The other test trial was the three step test, in which the familiar item was paired with a dissimilar item that was novel by three metric steps on the same dimension as the one step test. Note that the direction of the one and three step tests was in opposite directions on the continuous dimension (see Figure 20). The order of the one and three step tests was counterbalanced across infants. The dimension on which infants were tested (color or shape) was also counterbalanced across infants. Twenty-four infants were tested with the one step test first, and 26 were tested with the one step test second.

During the experimental session, infants sat on their parents lap 100 cm in front of the monitor. Parents wore opaque glasses to prevent parental bias. A trained observer sat behind the curtain and presented stimuli on the monitor. The observer also recorded infants' looking time on a computer while watching them on a black and white TV. At the beginning of each trial, a looming white circle on a gray background periodically produced a chirping sound. Once the observer determined that the infant was looking at this attention-getting stimulus, the observer pressed one computer key to present the stimuli, one computer key when the infant was looking left, and one computer key when the infant was looking right.

Results

A preliminary question that this study addressed was whether infants discriminate along a single, continuous feature dimension embedded within a multi-dimensional object. As a group, infants exhibited a novelty preference on the three step test (M=.58, SD=.13), $t(49)$=4.36, p<.001, and a null preference on the one step test, (M=.48, SD=.13), $t(49)$=-1.12, p>.1. These data closely match simulations results. When averaged across simulations, the model exhibited a novelty preference on the three step test, (M=.58, SD=.11), and a null preference on the one step test, (M=.48, SD=.12). These results indicate that infants, like the DNF model, can discriminate along a single, continuous feature dimension embedded within a multi-dimensional object.

Next I used hierarchical regression to examine whether individual variations in infants' looking behavior were related to test performance as in the DNF model. In particular, I performed the same hierarchical regression analyses on the infants as with the model. The first analysis showed that looking on the one step test accounted for a significant proportion of variance in novelty scores on the one step test, R^2=.08 (see Table 6). Like the DNF model, then, looking on the one step test is a good predictor of infants' performance on this fine-grained test. Next, I examined infants' performance on the three step test. Results are shown in Table 7. For the three step test, shift rate, look duration, and shift rate together were good predictors of performance on the three step test, R^2=.17. Looking on the one step test was not. These regression analyses on infants' looking and discrimination performance are remarkably similar to analyses of the DNF model. The DNF model not only predicted how looking measures are related to performance across two different discrimination contexts, but the strength with which looking measures were predictive of discrimination performance was comparable for infants and the model.

The critical prediction of the model is that robust memory can lead to familiarity bias under conditions where the familiar and novel item are similar. To probe this, I parsed infants into low and high groups based on median looking time on the one step test and examined the novelty scores. Results of the median split are shown in Figure 19 along side model results for comparison. On the one step test, infants in the low looking group exhibited a familiarity preference (A), and infants in the high looking group exhibited a null preference (D). On the three step test, infants in the low looking group exhibited a novelty preference (G), and infants in the high looking group exhibited a novelty preference (J). To test whether test order or test dimension interacted with infants' discrimination performance at test, I conducted a repeated measures analysis of variance (ANOVA) with test (one step, three step) as a within subjects factor and order (one step first, one step second) and test dimension (color, shape) as between subjects factors. The model only revealed a main effect of test, $F(1,46)=11.76$, $p<.001$. Infants exhibited stronger novelty scores on the three step test than on the one step test. For the primary analyses, the data were collapsed across test order and dimension.

Pre-planned t-tests were used to test the central predictions of the DNF model. Infants in the low looking group exhibited a statistically significant familiarity preference on the one step test, *t*(24)=-1.95, *p*<.05, one-tailed, but infants in the high looking group exhibited no reliable preference on the one step test, *t*(24)=.62, *p*>.1, one-tailed. Infants in the low looking exhibited a statistically significant novelty preference on the three step test, *t*(24)=2.68, *p*<.01, one-tailed, and infants in the high looking group also exhibited a statistically significant novelty preference on the three step test, *t*(24)=3.61, *p*<.001, one-tailed. As predicted, infants in the low looking group showed a robust familiarity bias late in learning when the familiar and novel items were similar, even when the one step test trial was presented *after* the three step test trial. In this case, then, infants showed a robust novelty-to-familiarity shift.

In addition to comparing performance of each group to chance levels, I also directly compared performance across the two types of test trials. A paired t-test comparing performance of the low looking group across test trials revealed a significant difference between preference scores on the one step and three step tests, *t*(24)=2.90, *p*<.01, two-tailed. This difference was marginally significant for the high looking group, *t*(24)=1.96, *p*=.06, two-tailed. Finally, I compared performance on the one step test across groups. An unpaired t-test revealed a marginal effect, with lower preference scores for the low looking group relative to the high looking group, *t*(48)=1.91, *p*=.06, two-tailed.

Looking on the one step test is a non-canonical index of individual differences in memory formation, but the DNF model predicted that this measure would be related to novelty preference scores. This measure is robustly linked to novelty preferences because it reflects the strength of memory – strong memory suppresses encoding of both the familiar and novel item, leading to little looking. As additional evidence that infants in the low looking group do have a relatively more robust memory of the familiar stimulus than infants in the high looking group, I evaluated whether infants in the low looking group exhibited a decline in looking from the first block of two trials to the last block of two trials. Infants in the low looking group looked 6.08 s in the first block and 5.12 s in last block on average. This decline in looking was statistically robust, $t(24)=2.22$, $p<.05$, two-tailed. Infants in the high looking group looked 6.71 s in the first block and 6.98 s in the last block on average. This change in looking was not statistically robust, $t(24)=-.70$, $p>.1$, two-tailed. These results provide additional evidence that infants in the low looking group do have a relatively stronger memory than infants in the high looking group.

Discussion

Visual foraging is an exploratory behavior that facilitates survival by locating novel items in the environment such as food and shelter. Foraging is also a mechanism by which knowledge about items in a visual scene is constructed. It is not surprising, then, that the novelty seeking aspect of foraging has been the focus of empirical research and theory. Novelty seeking is, after all, a signature of memory for items previously explored. This is reflected in theories of infant habituation and visual foraging in adults which assert that robust memory gives rise to recognition and novelty biases.

Existing theories, however, do not paint a clear picture of how the context influences familiarity biases. For instance, whether adults exhibit a familiarity or novelty bias depends on the task context (Dodd et al., 2009). When searching for an item in a visual scene, adults rarely re-fixate previously fixated and remembered items. When casually viewing a scene, by contrast, adults frequently re-fixate previously fixated and remembered items. Whether adults exhibit familiarity or novelty biases also depends on the stimulus context (Park et al., 2010). When viewing pairs of familiar and novel faces, adults exhibit a familiarity bias. When viewing pairs of familiar and novel scenes, adults exhibit a novelty bias. Related effects may generalize to infancy. For instance, whether infants exhibit a familiarity or novelty bias depends on the task context (Shinskey & Munakata, 2005). Infants are more likely to search for a remembered item in the dark and a novel item in the light, suggesting that robust memory might guide behavior toward familiarity in demanding task contexts.

Here, I showed that robust memory in the DNF model and 10-month-old infants led to a familiarity bias while looking at similar familiar and novel items and a novelty bias while looking at dissimilar familiar and novel items. These results show that in a difficult discriminatory context, infants' memory can guide their behavior toward familiarity.

The present investigation makes a unique contribution to a growing literature on infants' discrimination abilities. By 4 months of age, infants can discriminate between familiar and novel items that differ on two dimensions (e.g., a green cross from an orange circle), but not one dimension (e.g., a green cross from a green circle) (Cohen et al., 1971; see also Cornell & Strauss, 1973; Saayman et al., 1964; Welch, 1974). By 6 months of age, infants begin to respond to novel items that vary on one continuous, metrically organized magnitude dimension (e.g., area) embedded within multidimensional stimuli (Brannon et al., 2006; see also Brannon et al., 2007). Similarly, results reported here show that infants can discriminate along one continuous, metrically organized visual feature dimension embedded within a multidimensional object.

These data demonstrate that infants' response to novelty is influenced by the degree of discrepancy between familiar and novel items. There is debate in the literature, however, regarding precisely how discrepancy impacts discrimination. Some researchers have shown that response to discrepancy follows an inverted u-shaped pattern, where infants respond to low and high levels of discrepancy less than to medium levels of discrepancy (McCall & Kagan, 1967; McCall & Melson, 1969). This discrepancy hypothesis has been tested with stimulus sets such as circles and crosses that constitute a line, from which different levels of discrepancy are created by manipulating the verticality and linearity of the line. When infants are familiar with circles and crosses aligned vertically, they respond more to a 90° rotation of the alignment (medium discrepancy) than to a 45° rotation of the alignment (low discrepancy) or a compression of the linearity of alignment of the items (high discrepancy). The aforementioned pattern of results has not been consistently observed, however, which may be influenced by similarity between familiar and novel items, the particular dimension being remembered and discriminated along, or both. For example, Welch (1974) found that infants' response to novelty increased linearly as the number of dimensions between the familiar and novel item increased from one, to two, to three. Similarly, Brannon et al. (2006) found that infants' response to novelty increased linearly as the metric distance between the familiar and novel items increased. Here, I found that discrimination between similar items on color and shape dimensions surfaced as a familiarity bias. This result further complicates an already complex literature on infants' response to metric discrepancies.

Cross-study differences like those described above might arise from stimulus differences – infants' discrimination can differ as a function of dimension, for instance.

One challenge in understanding infants' discrimination abilities is controlling the stimulus dimensions to which they are exposed. I believe this is critical for understanding how infants' memory representations impact looking to familiar and novel items (see also French et al., 2004) and how different stimulus dimensions (e.g., magnitude, feature, spatial, etc.) impact memory formation and discrimination. Here, I used a stimulus set that consisted of continuous feature dimensions with well-controlled metric properties. I found that, as a group, 10-month-old infants exhibited a novelty bias when the familiar and novel items were metrically dissimilar. Most critically, infants with a robust memory exhibited a familiarity bias when the familiar and novel items were metrically similar. Note that Brannon et al. (2007) manipulated metric similarity but did not report the same pattern of results. This may reflect differences in the feature dimensions probed across studies. It is also possible this reflects task differences: I tested infants in the VPC, whereas Brannon et al. used a single presentation habituation task. Infants do perform differently in preferential looking than single presentation contexts (Oakes & Ribar, 2005). At present, however, such details are poorly understood. I contend that theoretical models, like the DNF, can foster understanding of this issue in future work.

The present investigation also makes at least four theoretical contributions to domains of infant memory and visual exploration. First, I used a model of adult visual working memory and change detection to capture infant memory (Johnson et al., 2009). This model captures basic perceptual and memory processes in a canonical probe of visual working memory—change detection. One advantage of using this model is that it establishes developmental continuity in these basic perceptual and working memory processes. Indeed, the comparison of percepts with items maintained in memory has been proposed to rely on working memory in infant looking tasks like the one used here (Oakes, Horst, Kovack-Lesh, & Perone, 2008; Oakes & Ribar, 2005; Ross-Sheehy et al., 2003). The DNF model provides a process level account of how items enter working memory, how working memory influences recognition, and how perception and working memory work together to discriminate old from new items (see also, Perone, Simmering, & Spencer, 2010).

Second, the DNF model provides an explanation for how memory can guide behavior toward familiarity (Dodd et al., 2009; Park et al., 2010; Shinskey & Munakata, 2005). In the DNF model, a bias to look at a familiar over a novel item can arise from robust memory in the context of a challenging, fine-grained discrimination. This happens, in part, because stimuli are encoded and remembered in neural populations that interact over continuous, metrically organized dimensions. This enables working memory for one item to suppress encoding of highly similar items, leading to very weak support for continued fixation. This also arises, in part, because repeated stimulation of neurons raises their baseline level of responding via Hebbian learning. In the context of a similar novel item, this biases the system to continue fixating a familiar item. This, in turn, fosters enhanced learning about the familiar relative to the novel item which may be adaptive in demanding situations.

These features of the DNF model enable robust memory to lead to a familiarity bias in one stimulus context and a novelty bias in another stimulus context. It is unclear whether or not a familiarity bias could arise from robust memory in existing models of infant looking and memory. Consider autoencoders as an example. An autoencoder consists of a small layer of hidden units sandwiched between identical input and output layers. With repeated presentation of a stimulus, the hidden layer begins to produce the stimulus input vector on the output layer. This leads to low levels of error between the input and output layers as an internal representation is formed. In autoencoders, low levels of error are said to reflect low levels of looking. When a similar novel item is presented, it leads to an increase in error as the hidden layer accommodates the new stimulus input. Because error increases when the novel item is presented, looking would increase as well and the model would show a novelty bias. It is unclear how autoencoders or models that operate on the same principles could be modified to exhibit a familiarity bias in the context of robust memory.

Third, the DNF model captures a rich set of looking dynamics measurable in the VPC. Remarkably, individual differences in looking were related to discrimination performance in similar ways in the DNF model and infants. Consistent with empirical findings, looking indices of processing speed were related to performance at test with a relatively easy discrimination (e.g., Rose et al., 2001; 2002). By contrast, a novel behavioral signature of robust memory—looking on the one step test—was related to performance on the one step test in both models and infants. Note that these individual differences emerged in the model without any parameter changes across simulations. In particular, the only difference across the 400 simulations conducted was stochastic fluctuations in the fixation and neural dynamics. Typically, individual differences in looking are described as a stable characteristic of the child's cognitive system, and there is good evidence to support this (Colombo & Mitchell, 1990; Rose et al., 2001; 2002; 2004). The present findings indicate that some individual differences emerge over the course of a task as infants stochastically distribute their looking among stimuli. In some respects, this is consistent with results from Jankowski et al. (2001) showing that simply manipulating the distribution of infants' looks influences their discrimination performance. The pattern of looking through time—whether emergent or influenced by the experimental context—may itself influence memory formation.

Finally, the DNF model complements ongoing neurophysiological research on infants' visual recognition abilities. There is some debate about whether recognition in looking tasks reflects implicit or explicit memory (for a discussion, see Rose, Feldman, & Jankowski, 2007; Snyder, 2007). A number of studies point toward an implicit memory view, showing that neuronal activity becomes suppressed as items become familiar to infants (e.g., Nelson & Collins, 1998). This, in turn, may be sufficient to bias infants to look away from familiar items and toward novelty. Consistent with this view, Snyder (2010; see also Snyder, 2007) found that a decrease in ERP amplitude during encoding was associated with stronger preferences for novelty during test. Similarly, in the DNF model, strong activity in WM suppresses activity in PF. This leads to recognition and biases the model toward novelty. The neural dynamics within DNFs have been used to predict ERP responses in adults (McDowell, Jeka, Schöner, & Hatfield, 2002). Thus, DNFs may provide a strong theoretical bridge between behavioral and ERP measures in future work.

It is unclear whether working memory is directly involved in repetition suppression, that is, a reduction of neuronal responding as a stimulus becomes familiar (for a discussion, see Desimone & Duncan, 1995). Recent fMRI studies examining the neural dynamics involved in the maintenance of items in working memory suggest that working memory can have this effect. For example, Todd, Fougnie, and Marois (2005) reported that the suppression of cortical networks involved in encoding increases as the number of items maintained in memory increases. These findings resemble the neural mechanisms of encoding and memory formation in the DNF model, with strong suppression of neural populations encoding remembered items over learning. Interestingly, Todd and Marois (2005) found that individual differences in the strength of activity within cortical working memory networks predicted performance in a change detection task. Similarly, I found here that strong activity in WM was associated with low levels of looking and enhanced discrimination between highly similar familiar and novel items. This suggests that a promising direction for future research will be to bring the DNF model together with neurophysiological measures of perceptual and memory processes.

In summary, in this chapter I generalized the DNF model from single presentation tasks to the VPC to capture a richer set of looking dynamics. I used the model to go beyond qualitative demonstrations of theoretical concepts to test the model empirically with infants. I found a remarkably similar relationship between looking and discrimination in the model and infants. Additionally, the empirical results showed that infants, like the DNF model, can discriminate along a single, continuous feature dimension embedded within a multi-dimensional object. This work takes an important step toward attaining a richer understanding of the link between looking and cognitive dynamics, the overarching goal of this thesis. This work also allows me to address one of the primary questions of this thesis: do looking and discrimination change together over development? In Chapter 5, I examine this question with infants and the generalized DNF model.

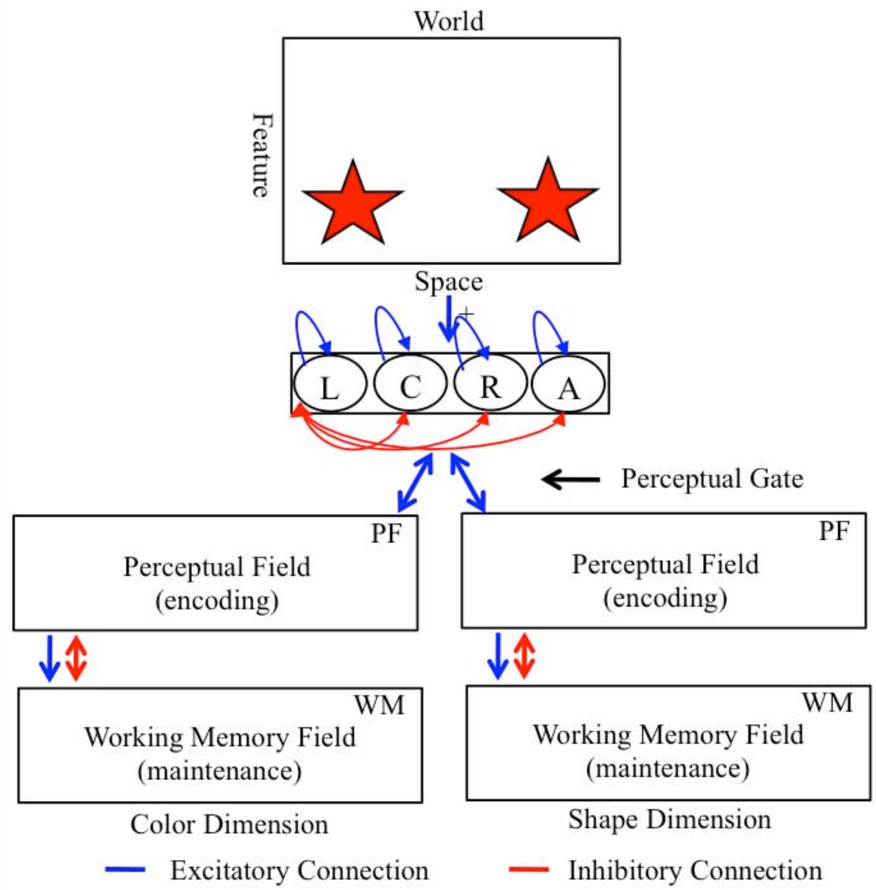
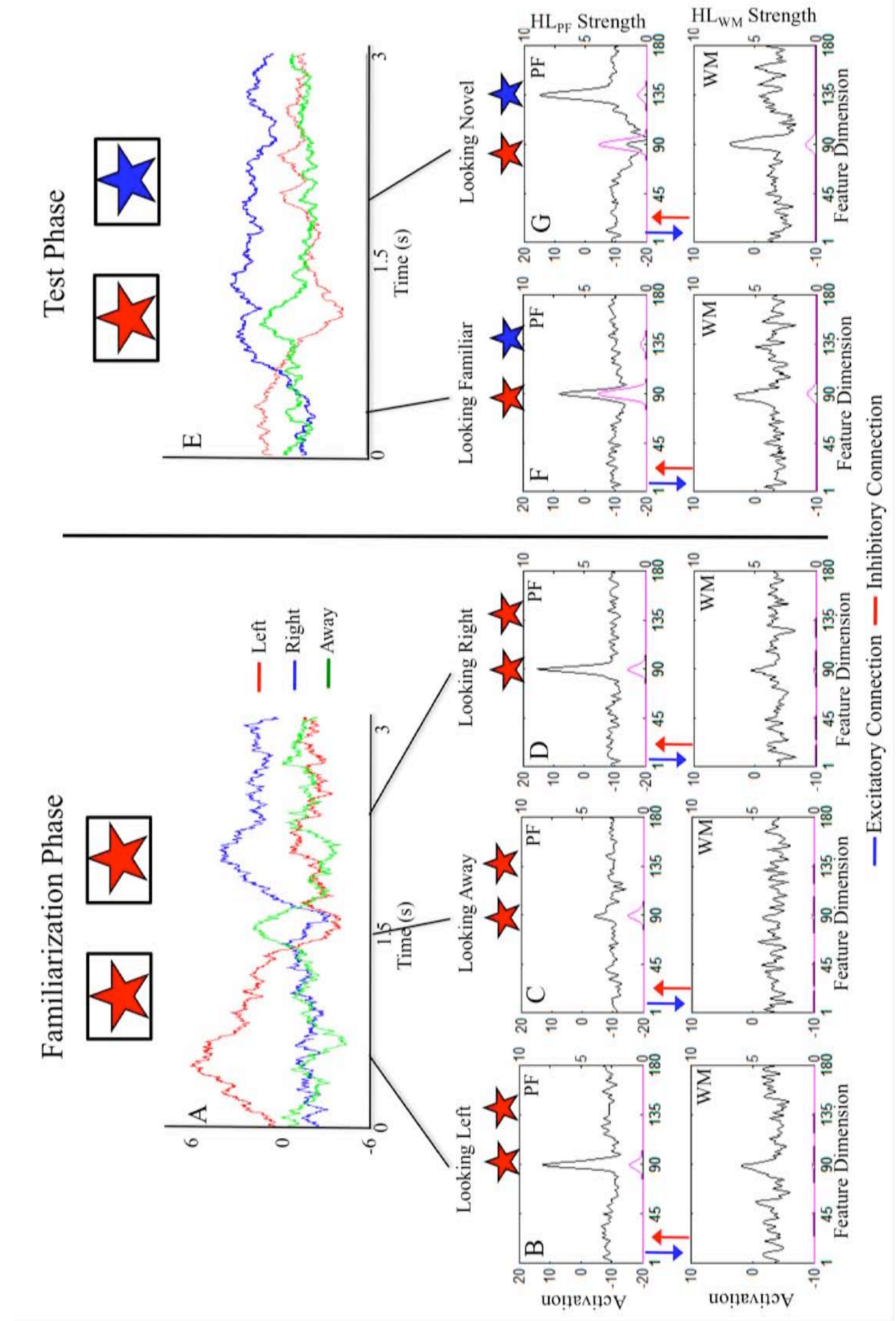


Figure 15. Generalized Dynamic Neural Field Model. Schematic of DNF model situated in visual paired comparison procedure. At the top is a world that contains identical multi-dimensional objects at left and right locations. The presence of objects in the task space presents noisy input to left and right nodes that compete for fixation via competitive, excitatory (blue arrows) and inhibitory (red arrows) interactions. When looking at a particular location, metric information is input into selectively tuned neurons within a PF tuned to one dimension (e.g., color) and a PF tuned to another dimension (e.g., shape).

Figure 16. Looking and Learning In Visual Paired Comparison. Illustrates how the DNF model looks and learns in the VPC during familiarization (left) and test (right) phases. The model stochastically looks among left (red line), right (blue line), and away (green line) locations (A). During familiarization, when looking left, the stimulus is input into PF (B). Via noise, the model switches gaze and begins to look to away locations. While looking away, PF activity subsides (C). Across fixations, the model encodes identical items (red stars) upon fixating each location. Thus, when the model switches gaze again and looks right, the stimulus is input into PF (D). During test, (in this example) the model looks left and then right (E). When looking left, the familiar item is input into PF (F). Working memory is strong and encoding in PF is weak. This leads the model to release fixation to the left location, and the model switches gaze to look right (see E). When looking right, the novel item (blue star) is input into PF. Activation in PF is strong because the novel item excites neurons in PF that are uninhibited by WM. This leads the model to look longer at the novel item, that is, the model exhibits a novelty preference.


Familiarization Phase
Test Phase
A
E
6
0
-6
0
1.5
3
Time (s)
Left
Right
Away
Looking Left
Looking Away
Looking Right
Looking Familiar
Looking Novel
B
C
D
F
G
PF
WM
Activation
20
10
0
-10
-20
1
45
90
135
180
Feature Dimension
HL$_{PF}$ Strength
HL$_{WM}$ Strength
5
Excitatory Connection
Inhibitory Connection

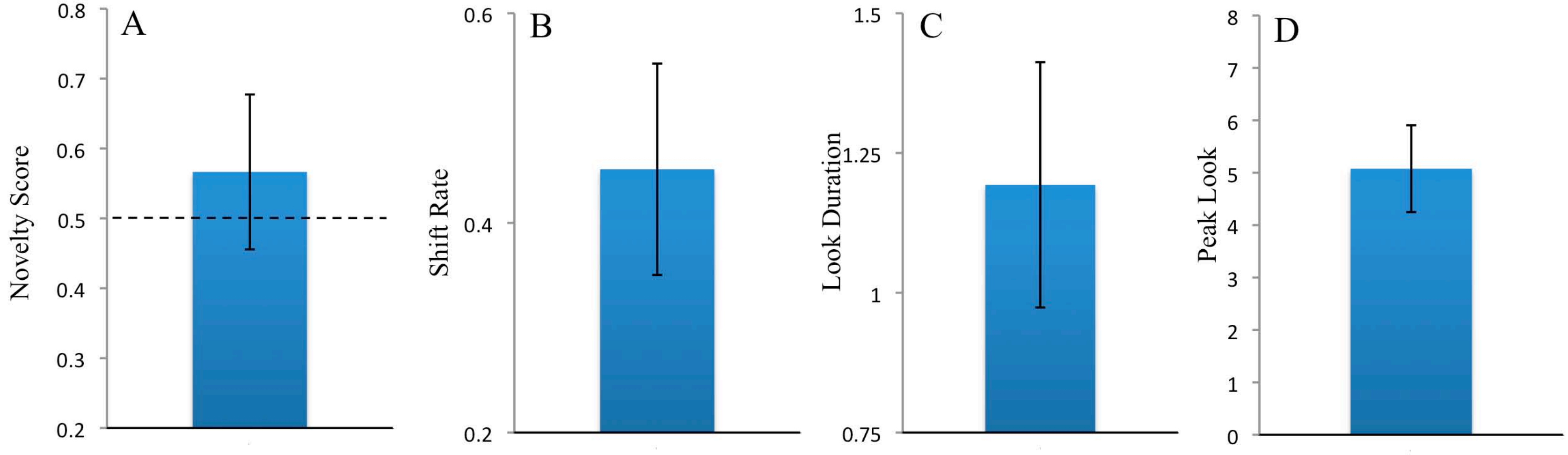


Figure 17. Looking Measures From Visual Paired Comparison. Shows common looking measures from the VPC produced by the DNF model. From the model's looking behavior, novelty score (A), shift rate (B), look duration (C), and peak look (D) measures can be calculated in the same ways as they are for infants. Error bars are 1 SD.

Figure 18. Memory Induced Familiarity Bias. Panel A shows the state of PF and WM early in learning when looking at pairs of identical items. Activation in PF generated when looking is strong (black line, left y-axis) and activation in LTM_{PF} begins to accrue (purple line, right y-axis). Activation in WM (black line, left y-axis) and LTM_{WM} is weak. Looking time across pairs of identical items early in learning is high. Panels B-C show the source of novelty preferences when looking at a dissimilar novel item (B) and a familiar item (C). Activity in PF is strong when looking at a metrically dissimilar item relative to activity in PF when looking a familiar item. This gives rise to a novelty bias. Looking time is relatively higher than looking at pairs of identical items late in learning. Panels C-D show the sources of familiarity preferences in the context of robust memory when looking at a similar novel item (D) and a familiar item (C). Activity in PF is strong when looking at the familiar item relative to activity in PF when looking at the similar novel item. The similar novel item stimulates strongly inhibited neurons in PF by WM via Inhib (not shown). PF responds more strongly when looking at the familiar item because HL_{PF} is robust late in learning and facilitates activity (see purple line, right y-axis). Note that looking time across the familiar item and similar novel item is low.

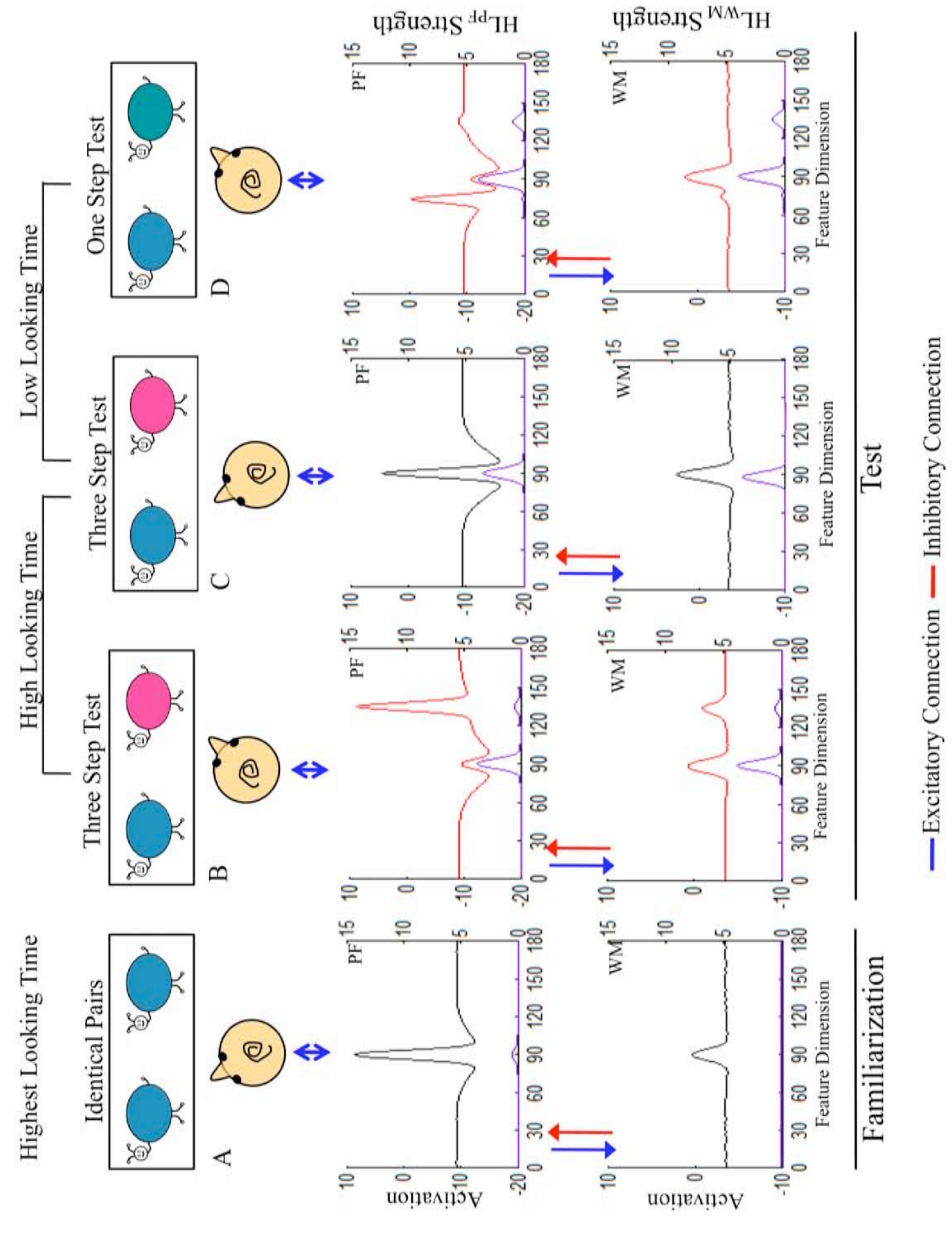

Highest Looking Time
High Looking Time
Low Looking Time
Identical Pairs
Three Step Test
Three Step Test
One Step Test
A
B
C
D
PF
WM
Activation
Activation
10
0
-10
-20
15
10
5
0
0 30 60 90 120 150 180
Feature Dimension
HL_{PF} Strength
HL_{WM} Strength
Familiarization
Test
Excitatory Connection
Inhibitory Connection

Table 2. Model Parameters Visual Paired Comparison

PF(u)		WM(w)		Inhib(v)		Fixation(f)		Time Scales (τ)		Hebbian Learning (hl)	
h_u	-10.20	h_w	-3.57	h_v	-10.20	c_{ci}	3.50	τ_{excite}	80	c_{hl}	2.20
c_{uu}	0.85	c_{ww}	0.97	c_{uv}	0.70	c_{ff}	1.20	τ_{inhib}	10	σ_{uhl}	3.00
σ_{uu}	3.00	σ_{ww}	3.00	σ_{uv}	15.00	c_{fu}	0.35	τ_{build}	15000	c_{whl}	0.30
		c_{wu}	0.20	c_{vu}	0.80	c_{uf}	1.00	τ_{decay}	100000	σ_{whl}	3.00
		σ_{wu}	5.00	σ_{vu}	5.00	c_b	1.00				
				c_{wv}	0.07	c_{ag}	5.50				
				σ_{wv}	13.00	c_s	6.50				
				c_{vw}	3.00	c_{sa}	6.50				
				σ_{vw}	5.00	h_{rest}	5.00				
						h_{down}	6.00				

Table 3. Predicting Working Memory Strength In Model

DNF Working Memory Strength							
Step	**Predictors**	***R^2***	***R^2* Change**	***F* Change**	***p***	B	***p***
1	Shift Rate Look Duration Peak Look	.007	.007	.88	.45	-1.34 <.0001 .12	.4 .87 .78
2	Looking One Step	.044	.038	15.64	<.0001	-.40	<.0001
3	Order	.08	.035	15.02	<.0001	-.77	<.0001

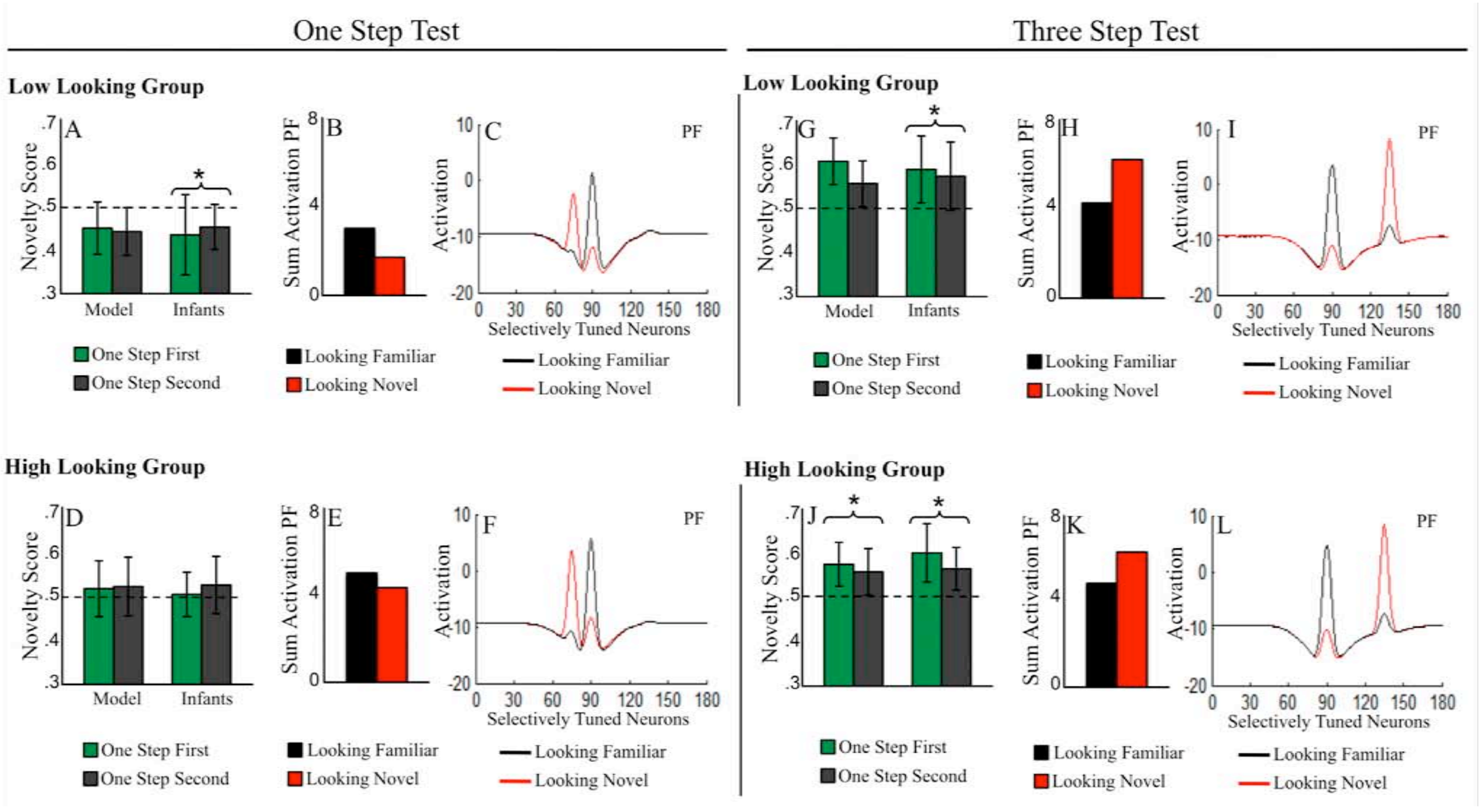
Table 4. Predicting One Step Novelty Score In Model

DNF One Step Novelty Score							
Step	**Predictors**	***R***^{2}	***R***^{2} **Change**	***F*** **Change**	***p***	B	***p***
1	Shift Rate	.012	.012	1.64	.18	.11	.26
	Look Duration					.04	.35
	Peak Look					<.0001	.07
2	Looking One Step	.093	.081	35.21	<.0001	.04	<.0001
3	Order	.095	.002	.71	<.40	.01	.40

Table 5. Predicting Three Step Novelty Score In Model

DNF Three Step Novelty Score							
Step	**Predictors**	***R^2***	***R^2* Change**	***F* Change**	***p***	B	***p***
1	Shift Rate	.021	.021	2.80	.04	-.18	.05
	Look Duration					-.10	.02
	Peak Look					<.0001	.28
2	Looking One Step	.026	.005	2.14	.14	.01	.14
3	Order	.03	.004	1.76	.19	-.02	.19

Figure 19. Model Predictions and Experiment 1 Results. Panels A-C shows the preference scores for the low looking group (A), sum of activity in PF while looking at each item, and (C) the state of PF when looking at a familiar stimulus relative to the novel one step test. Activity in PF is relatively stronger when looking at the familiar than the novel item, giving rise to a familiarity bias regardless if the one step test was presented first or second. Panels D-F shows the same data for the high looking group when looking on the one step test. Activity in PF is comparable when looking at the familiar and one step test. The model and infants did not show a robust preference. Panels G-H shows the same data for the low looking group when looking on the three step test. Activity in PF is relatively stronger for the novel three step item than the familiar item. The model and the infants exhibited a novelty preference. Similar dynamics were observed for the high looking group on the three step test (J-L). Error bars are 1 SD. * significant one-sample t-test.


One Step Test
Three Step Test
Low Looking Group
High Looking Group
A
B
C
D
E
F
G
H
I
J
K
L
Novelty Score
.7
.6
.5
.4
.3
Model
Infants
*
One Step First
One Step Second
Sum Activation PF
8
4
0
Looking Familiar
Looking Novel
Activation
10
0
-10
-20
PF
0
30
60
90
120
150
180
Selectively Tuned Neurons

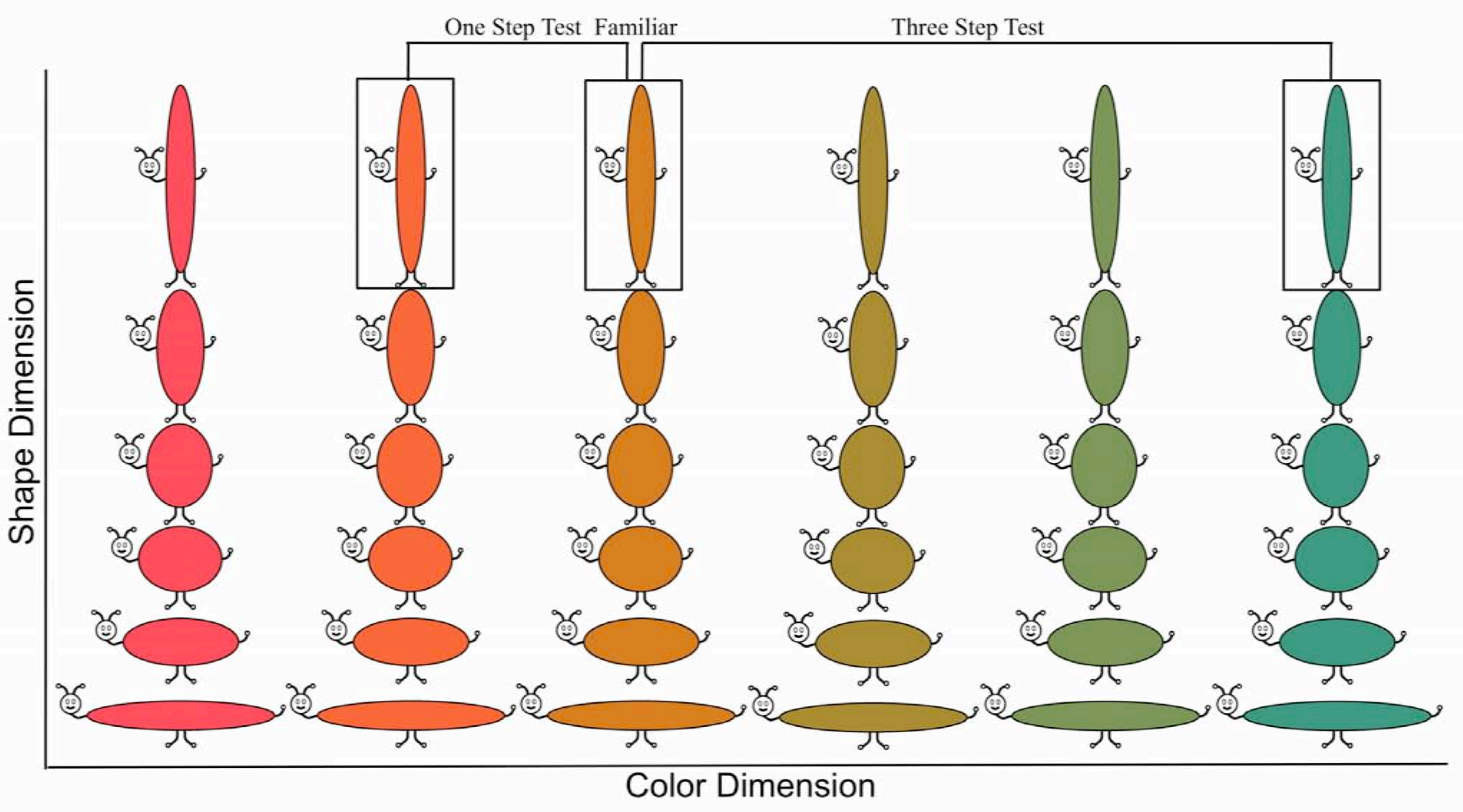


Figure 20. Metrically Organized Stimulus Set. Two-dimensional stimulus set based on continuous, metrically organized color and shape dimensions. Shows sample of 6 of 12 colors. Boxes illustrate experimental design.

Table 6. Predicting One Step Novelty Score In Infants

10 Mo One Step Novelty Score							
Step	**Predictors**	R^2	R^2 **Change**	F **Change**	p	B	p
1	Shift Rate	.002	.002	.02	1.00	-.01	.98
	Look Duration					.004	.96
	Peak Look					.002	.90
2	Looking One Step	.083	.081	3.98	.05	.01	.05
3	Order	.090	.008	.37	.55	.03	.55

Table 7. Predicting Three Step Novelty Score In Infants

10 Mo Three Step Novelty Score							
Step	**Predictors**	***R^2***	***R^2* Change**	***F* Change**	***p***	B	***p***
1	Shift Rate	.167	.167	3.06	.04	-.27	.09
	Look Duration					.02	.84
	Peak Look					-.03	.01
2	Looking One Step	.167	.000	.003	.96	<.0001	.96
3	Order	.180	.014	.727	.40	-.033	.40

CHAPTER 5

DEVELOPMENTAL CHANGE IN SPEED OF PROCESSING AND DISCRIMINATION

In the previous chapters, I developed a new theory of infant looking and memory formation and empirically tested a novel prediction of the theory. In particular, in Chapter 3, I showed that the DNF model overcomes several limitations of existing models of habituation. One key limitation of existing models is that they have not captured developmental changes in processing speed and discrimination within the same architecture. This limitation has precluded models from specifying whether developmental changes in processing speed and discrimination arise from the same or a different mechanism. I showed that the DNF model captures both types of developmental change. Critically, both arise from the same mechanism.

In Chapter 4, I generalized the DNF model to a more complex and ecologically valid task context—visual paired comparison. In the VPC task, infants explore multiple objects and exhibit rich patterns of looking dynamics that are meaningfully linked to cognitive processes. One goal was to investigate whether infants, like the DNF model, discriminate items that differ along a single continuous, metrically organized feature dimension embedded within a multi-dimensional object. Empirical results showed that infants do make such discriminations. In addition, I found that individual differences in looking were linked to discrimination performance in both the model and infants.

The current chapter has three goals. The first goal is to investigate whether developmental change in discrimination along the metric feature dimensions of color and shape parallels developmental change in discrimination along magnitude dimensions, that is, do infants exhibit an increased ability to discriminate along a metrically organized feature dimension with age. Recall that infants make increasingly subtle discriminations with age along magnitude dimensions such as temporal duration (Brannon et al., 2007). Similarly, Lipton and Spelke (2003) found that infants exhibited an increased ability with age to discriminate between numbers of sounds. These findings suggest that an ability to make increasingly subtle discriminations with age is a domain general developmental achievement. It is notable, however, that developmental change in discrimination has only been tested on magnitude dimensions. It is unknown whether infants also make increasingly subtle discriminations with age on visual feature dimensions such as color and shape.

The second goal of this chapter is to examine whether looking indices of processing speed and discrimination change together over development, and whether they are linked within individuals. Brannon et al. (2007) found that older infants habituated more quickly than young infants and discriminated between highly similar familiar and novel stimuli. However, in a replication they found no differences during habituation but a difference in discrimination still remained. Importantly, probing whether looking and discrimination change together over development was not the goal of their study. Moreover, they used an infant-control procedure that may have masked any relationships between looking and discrimination (for a discussion of looking in this procedure, see Cohen & Menten, 1981; Perone & Spencer, 2010). In another study, Rose et al. (2001) found that individual differences in shift rate, peak look, and look duration were all related to recognition performance. This finding might indicate that discrimination and processing speed are linked within individuals. However, disentangling discrimination and recognition can be difficult. Strong memory can impact recognition and novelty biases, but this may not be related to fine-grained discrimination per se. Moreover, Rose et al. used high-dimensional items that varied on multiple dimensions rather than items that have well-controlled metric properties. Such stimuli are less suitable for studying developmental change in discrimination because it can be ambiguous what novelty preferences are based on. Here, I use a stimulus set with well-controlled stimulus properties that is more suitable for studying changes in discrimination abilities over development.

The last goal of this chapter is determine whether implementing the SPH in the DNF model can capture developmental change in looking dynamics and discrimination in the VPC. Chapter 3 showed that the SPH qualitatively captures developmental change in both looking and discrimination in a single presentation task. Chapter 4 showed that the DNF model can quantitatively capture the looking and memory dynamics of infants and make novel predictions in the VPC. Here, I aim to capture a range of looking behaviors across development in quantitative detail to take an additional step toward the overarching goal of this thesis—to attain a richer understanding of the link between looking and cognitive dynamics in the first year.

I pursued these goals in two steps. First, I tested 5-, 7-, and 10-month-olds' discrimination between a familiar item and a similar (one step test) and dissimilar (three step test) item. In Experiment 1 (see Chapter 4), I observed that infants exhibited robust discrimination on the three step test. One question addressed here is how discrimination on the three step test changes over development. In Experiment 1, I also observed that individual differences in looking were linked to fine-grained discrimination on the one step test and discrimination on the three step test. Another question addressed here, then, is whether individual differences in looking predict discrimination performance across development. The second step was to implement the SPH in the DNF model in an effort to capture developmental change in looking and discrimination performance observed in the present experiment. This addresses the question of whether a single mechanism underlies developmental changes in these two behavioral measures.

Experiment 2

Method

Participants. Forty-five 5-month-old infants (*M*=170.31 days, *SD*=13.28 days), 39 7-month-old infants (*M*=230.31 days, *SD*=7.74 days), and 35 10-month-old infants (*M*=303.11 days, *SD*=11.43 days) participated in this study. The data for 24 of the 10-month-old infants were reported in Chapter 4.

Stimuli, design, and procedure. The stimuli, design, and procedure were identical to Experiment 1 with one exception. All infants were presented with the one step test first and the three step test second. Typically in the infant cognition literature, primary tests of interest are presented first. This reduces one source of variance in infants' test performance and, presumably, maximizes the likelihood that positive behavioral responses will be observed on critical tests. It also reduces sample size.

Results

Analyses are presented across three sections examining developmental change in discrimination, developmental change in looking indices of processing speed, and the link between individual differences in processing speed and discrimination. Preliminary analyses revealed no effect of test dimension on test performance. Thus, data were collapsed on this variable.

Familiarization. My first set of analyses examined developmental change in total looking during the familiarization phase and looking across the first and last block of two familiarization trials. These measures provide a general characterization of infants' looking commonly examined in single presentation tasks. Figure 21A-B shows the mean total looking time (A) and looking on the first and last block (B) across development. I first evaluated total looking time statistically. A one-way ANOVA revealed that total looking time differed across age, $F(2,116)=4.35$, $p<.05$. Post-hoc comparisons revealed that total looking time was shorter at 10 months of age ($M=34.90$ s, $SD=7.35$) than at 5 months ($M=39.82$ s, $SD=8.66$), $p<.05$, and total looking time was shorter at 7 months of age ($M=35.15$ s, $SD=9.52$) than at 5 months, $p<.05$. Infants exhibited less looking time overall with age.

Next, I evaluated how looking across the first and last block change over development. To examine this, I conducted a repeated-measures ANOVA with block (first, last) as a within-subjects factor and age (5, 7, 10) as a between-subjects factor. The test revealed an age x block interaction, $F(2,116)=3.01$, $p=.05$. Tests of simple effects revealed that infants exhibited a decline in looking from the first to last block at 10 months of age, $F(1,116)=4.32$, $p<.05$, a marginal decline at 5 months of age, $F(1,116)=3.47$, $p<.10$, but no decline at 7 months of age, $F(1,116)=1.06$, $p>.1$.

Next, I examined developmental change in three looking indices of processing speed – shift rate, look duration, and peak look during familiarization. Figure 22A-C shows these indices across development. I evaluated developmental change in these looking measures using one-way ANOVAs. The test for shift rate revealed a significant effect of age, *F*(2,116)=3.16, *p*<.05. Post-hoc comparisons revealed that shift rate at 10 months of age (*M*=.53, *SD*=.16) was faster than at 5 months of age, (*M*=.42, *SD*=.25), *p*=.05. The ANOVA for look duration also revealed a significant age effect, *F*(2,116)=7.19, *p*<.001. Post-hoc comparisons revealed that look durations were shorter at 10 months of age (*M*=1.28 s, *SD*=.29) than at 5 months (*M*=1.95 s, *SD*=1.26), *p*<.01, and shorter at 7 months of age (*M*=1.41 s, *SD*=.56) than at 5 months, *p*<.05. Finally, there was a significant age effect for peak look, *F*(2,116)=8.43, *p*<.0001. Post-hoc comparisons revealed that peak looks were shorter at 10 months of age (*M*=3.85 s, *SD*=1.70) than at 5 months (*M*=5.6 s, *SD*=2.61), *p*<.001, and shorter at 7 months of age (*M*=4.08 s, *SD*=1.78) than at 5 months, *p*<.01. These results indicate that there were robust changes in looking indices of processing speed over development, most dramatically between 5 and 7 months of age.

Test. To determine whether discrimination performance interacted with test dimension over development, I conducted a repeated measures ANOVA with novelty score at test (one step, three step) as a within subjects factor and age (5, 7, 10) and dimension (shape, color) as between subjects factors. There were no significant effects. To increase power, I collapsed across test dimension for my primary analyses. I conducted two sets of analyses on infants' looking behavior during the test phase. The first set of analyses centered on infants' discrimination performance on the one and three step tests. Infants' novelty scores on the one and three step tests are shown in Figure 23A. To determine whether infants exhibited novelty scores significantly greater than chance on the one and three step tests, I conducted a series of two-tailed, one-sample t-tests.

Infants did not exhibit a reliable preference on the one step test at 5 months of age, $t(44)=-1.26$, $p>.1$, 7 months of age, $t(38)=.92$, $p>.1$, or 10 months of age, $t(35)=-.64$, $p>.1$. On the three step test, 5-month-olds also did not exhibit a reliable preference, $t(44)=1.06$, $p>.1$. However, infants exhibited a reliable novelty preference on the three step test at 7 months of age, $t(38)=3.50$, $p<.001$, and 10 months of age, $t(34)=3.29$, $p<.01$. These results show an increased ability to discriminate along a continuous, metrically organized feature dimension with age.

I also assessed whether there were any differences in test performance across development using a repeated measures analysis of variance (ANOVA). Test type (one step, three step) was a within-subject factor and age (5, 7, 10) was a between-subjects factor. Results revealed a main effect of test type, $F(1,116)=11.35$, $p<.001$, with higher novelty scores on the three step test (see Figure 19A). There was also a marginal main effect of age, $F(2,116)=.2.78$, $p=.07$. Post-hoc comparisons revealed that 7-month-olds exhibited a higher novelty score ($M=.55$, $SD=.10$) than 5-month-olds ($M=.5$, $SD=.011$), $p=.05$. Consistent with other findings from the visual recognition literature, therefore, infants exhibit stronger preferences for novelty with age.

The next set of analyses examined whether shift rate and look duration during the test trials differed over development. Figure 24A-B shows shift rate (A) and look duration (B) on the one and three step tests across development. To evaluate shift rate, I conducted a repeated measures ANOVA with test (one step, three step) as a within-subjects factor and age (5, 7, 10) as a between-subjects factor. There was a significant test x age interaction, $F(2,116)=3.43$, $p<.05$. Test of simple effects revealed that infants exhibited a higher shift rate on the three step test than the one step test at 10 months of age, *F*(1,116)=9.48, *p*<.01, but infants exhibited no differences in shift rate across the tests at 5 months of age, *F*(1,116)=.11, *p*>.1, or 7 months of age, *F*(1,116)=.07, *p*>.1.

I evaluated look duration using the same method. The test revealed a marginal age x test interaction, *F*(2,116)=2.36, *p*=.10. Test of simple effects revealed that infants exhibited a trend toward shorter look durations on the three step test than the one step test at 10 months of age, *F*(1,116)=2.95, *p*<.10, but infants exhibited no differences in look duration across test trials at 5 months of age, *F*(1,116)=.29 *p*>.1, or 7 months of age, *F*(1,116)=1.50, *p*>.1. In summary, infants showed robust discrimination on the three step test at 7 and 10 months of age, but not at 5 months of age. Moreover, looking dynamics across the one and three step tests differed at 10 months of age with an increase in shift rate and a decrease in look duration from the one to three step test. Below, I will show that these looking dynamics arise from subtle transitions in the state of memory across the test phase in the DNF model.

Individual Differences. The analyses on infants' data indicate that processing speed increases over development. Similarly, there is an increased ability to discriminate along a continuous, metrically organized feature dimension over development. But are these changes related within individuals? To probe this, I conducted a series of hierarchical regressions to test whether looking indices of processing speed accounted for a significant proportion of variance in novelty scores on the one and three step test trials. Note that I did not examine individual differences by parsing infants into groups based on median spits, as in Experiment 1. Instead, I used regression to examine the link between individual differences in looking and discrimination. Regression is a more sophisticated tool for examining how variables covary and depends less on the range of variability of a given variable, such as the novelty score. Additionally, the key question in Experiment 1 was whether infants with robust memory exhibited a familiarity bias in a demanding discriminatory context. Answering this question requires evaluating whether infants exhibited a novelty score significantly different from chance. Here, the key question is whether processing speed and discrimination are linked within individuals, which does not require infants, as a group, exhibit novelty scores significantly different from chance.

The first analysis examined whether looking measures predict performance on the one step test above and beyond age. In the first step, I entered age as a predictor and novelty score on the one step test as the dependent measure. Results are shown in Table 8. Age did not account for a significant proportion of variance in novelty scores on the one step test. However, looking indices of processing speed - shift rate, look duration, and peak look – did account for a significant proportion of variance in novelty scores on the one step test, R^2=.08. Evaluating the beta weights indicates that shift rate is the strongest predictor in the context of the others. It is notable that the slope of the beta weight is negative, indicating that lower novelty scores (familiarity preferences) were associated with faster shift rates. This is consistent with the notion put forth in Chapter 4 that strong memory induces a familiarity bias on this fine-grained test. Peak look was also a marginal predictor. In contrast to shift rate, however, the negative beta weight suggests that longer peak looks were associated with lower novelty scores on the one step test. This contrasts with typical notions of peak look, that is, that short peak looks reflect fast processing.

In the last step, I evaluated whether total looking time on the one step test accounted for a significant proportion of variance in novelty scores on the one step test.

In contrast to Chapter 4, this measure was not a significant predictor. It is possible that the relationship between looking on the one step test and novelty scores revealed in Chapter 4 does not hold at younger ages (although a separate hierarchical regression did not reveal a significant interaction between looking on the one step test and age). It is also possible that this relationship is influenced by the order of test trials. Recall that the one and three step tests were not counterbalanced here.

In the next analysis, I conducted the same regressions on data from the three step test. Results are shown in Table 9. The model was not significant on any step, that is, neither age nor looking measures were predictive of performance on the three step test.

In summary, analyses of one step test performance revealed that looking indices of processing speed and discrimination change together over development and are linked within individuals. These results are consistent with the DNF model, which posits that processing speed and discrimination arise from the same developmental mechanism. These data are also consistent with data from Chapter 4 showing that processing speed and discrimination are robust within individuals in both the model and infants, although the nature of this relationship differed here. In the next section, I expand on these findings and probe whether the DNF model situated in the VPC can capture the co-development of processing speed and discrimination in quantitative detail.

Model Simulations

Method

The goal of the model simulations was to test whether the SPH could capture developmental change in looking and discrimination performance in the VPC. Toward this end, I tested whether the DNF could capture an array of looking measures over development. In particular, I aimed to capture 6 measures from familiarization at each age (18 total) including total looking, looking on the first and last block of two trials, shift rate, look duration, and peak look. I also aimed to capture 3 measures from each test trial at each age including novelty score, shift rate, and look duration (18 total). Across all three age groups, then, the total number of data points to be captured was 36.

The first step in modeling the data from Experiment 2 was to evaluate whether the parameters used in Chapter 4 with 10-month-olds were suitable for the larger number of variables to be captured with 10-month-olds here. Recall that I did not quantitatively model looking measures from familiarization in Experiment 1. The model generally captured infants' performance on a variety of measures. However, the model produced a qualitatively different pattern of shift rate across the one and three step tests. In particular, 10-month-olds in Experiment 2 showed an increase in shift rate across the one and three step tests, but the model produced the opposite pattern. This makes some sense in the model. When the model looks at the familiar stimulus on the one step test, activation in PF is quickly suppressed by WM. This leads the model to release fixation and switch gaze. When the model looks at the novel stimulus on the one step test, activation in PF is also quickly suppressed by WM. This again leads the model to release fixation and switch gaze. Across gaze shifts, then, the model accumulates a high shift rate. When the model looks at the novel stimulus on the three step test, by contrast, activation in PF is strong and provides support for fixation. This slows the release of fixation and gaze switching, leading to a lower shift rate. The difference in shift rate across the one and three step tests, then, reflects a meaningful relationship among interactions between PF, WM, and the fixation system in the model.

The question posed here, however, is whether the model can also show the opposite pattern at test, that is, the higher shift rate on the three step test shown by 10-month-old infants in Experiment 2. To examine this, I modified the parameters for the 10-month-old model to qualitatively reverse the pattern of shifting across the one and three step tests to gain a better understanding of the dynamics that underlie this behavior. As I discuss below, modification of the model's parameters did produce the opposite shift rate pattern at test. Thus, I present these new 10-month-old parameters in the sections below.

A critical question before discussing the simulation results, however, is whether these new 10-month-old parameters still produce the novel prediction tested in Experiment 1, that is, that infants who exhibit low levels of looking on the one step test also exhibit a familiarity preference on the one step test. To examine this, I re-simulated Experiment 1 with the new parameter set and parsed simulations into low and high looking groups based on total looking time on the one step test. As is shown in Figure 25B, low looking simulations exhibited a familiarity preference on the one step test, and both groups exhibited a novelty preference on the three step test. The data for 10-month-old infants from the current sample are also shown for comparison. Only low looking 10-month-olds in Experiment 2 exhibited a familiarity preference on the one step test, and both groups of infants showed a novelty preference on the three step test. Thus, the DNF model with the new parameter settings produces the same pattern of results across Experiments 1 and 2, and these results, once again, provide a good quantitative match to 10-month-olds' performance.

The next step in testing whether the SPH can capture developmental change in looking and discrimination was to implement the SPH in the model using the same method as in Chapter 3 for the single presentation task (see also Schutte & Spencer, 2009). Recall that the SPH posits that the strength of excitatory and inhibitory interactions increase over development. To implement the SPH, I began with the new 10-month-old parameters and worked backward in development. In particular, I weakened self-excitation in PF (c_{uu}) and WM (c_{ww}) as well as the strength of inhibition from Inhib to PF (c_{uv}) and to WM (c_{wv}) to create 7- and 5-month-old models. As in previous chapters, 200 simulations were run for each age group to produce robust model results. Parameter settings are shown in Table 10.

Results

I describe the model results across three sections. In the first section, I present model results from the familiarization phase. Next, I present model results from the test phase. In the last section, I present regression analyses on the model testing whether looking indices of processing speed in the model, like infants, is predictive of discrimination performance.

Familiarization. The DNF model captured global patterns of looking over development quite well. Figure 21 shows total looking time accumulated during the familiarization phase and looking during the first and last block for infants (A-B) and the model (C-D). Over development, total looking time in the model (C) and infants (A) declined. The decline was most dramatic between 5 and 7 months of age for infants and the model. The model did not capture the pattern of looking across the first and last blocks (D). The 10-month-old model, like 10-month-old infants, did exhibit a slight decline from the first to last block. By contrast, the 5-month-old model exhibited a slight increase in looking from the first to last block while 5-month-old infants exhibited the reverse pattern. Note, however, that the total looking time in each block was in the right quantitative range across ages.

What is the source of the developmental decline in total looking in the DNF model shown in Figure 21C? This decline reflects an increase the speed of working memory formation and the overall strength of working memory over development as shown in Figure 26. The top portion of the figure shows the sum of PF activity when the model looked at the familiar stimulus across trials. For the 5-month-old model (A), PF activity showed an increase over trials that was stronger than the increase for the 7- (B) and 10-month-old (C) models. This increase reflects the accumulating strength of the Hebbian contribution to PF. Notably, both the 7- and 10-month-old models show a decline in PF activity late in familiarization as working memory becomes more robust (see lower panels of Figure 26E-F). This reliably releases fixation and the model shows an overall decline in total looking.

The next simulation results are shown in Figure 22 which shows three looking indices of processing speed for infants (A-C) and the model (D-F). As the strength of neural interactions increased, the model exhibited a higher shift rate (D), shorter look durations (E), and shorter peak looks. Notice that the model captured the developmental pattern in some detail – the decline in look duration from 5 to 7 months of age, for instance, was steeper than from 7 to 10 months of age. These developmental changes in looking dynamics are once again evident in the neural dynamics captured in Figure 26. The strong WM peaks for the 7- and 10-month-old models led to relatively quick suppression of PF activity while looking at the familiar stimulus. This led to a high likelihood that the model would switch gaze, have short look durations, and short peak looks.

Test. The model results from the familiarization phase show that the SPH can capture developmental changes in looking indices of processing speed. Can the DNF model with the same developmental parameters also capture changes in discrimination? Recall that infants' exhibited a robust novelty preference on the three step test at 7 and 10 months of age, but not 5 months of age. As can be seen in Figure 23B, the 7- and 10-month-old models, but not the 5-month-old model, exhibited a robust novelty preference on the three step test.

These developmental differences arise from a shift in the contribution of PF activity associated with the familiar and novel stimulus over development. Figure 27A-C shows the sum of PF while looking at the familiar (black bar) and novel (red bar) items across development. For the 5-month-old model (A), PF activity was comparable while looking at the familiar and novel items. This led to a null preference overall. For the 7- (B) and 10-month-old (C) models, PF activity associated with the novel item was stronger than the familiar item. This led to a novelty preference.

The developmental shift in PF activity associated with the familiar item arises from a shift in the interaction between PF and WM. This can be seen in the bottom portion of Figure 27, which shows the state of PF and WM while looking at the familiar (black line) and novel (red line) stimulus on the three step test across development. When the 5-month-old model looks at the familiar and novel stimulus (D), activation associated with each stimulus is quite similar. For the 7- (E) and 10-month-old (F) models, however, activation is stronger while looking at the novel item than while looking at the familiar item. This has two sources. First, WM activity associated with the familiar item is supra-threshold during the test trial (see red line at site 90 in WM). This produces inhibition in PF. Second, PF activity associated with the novel item is sustained because updating of WM is slowed due to competition with the familiar item. Notice that WM activity associated with the novel item is stronger in the 5-month-old model than the 7- and 10-month-old model. This happens because activation in WM grows from a lower level in the older models.

The same analysis of the model's performance on the one step test is shown in Figure 28. Here, activation in PF associated with the familiar item was stronger than on the three step test for the older models. This led the 10-month-old model to dwell longer on the familiar item during the one step test relative to the three step test, leading to longer look durations and a lower shift rate. This is shown in Figure 24C-D. Although the developmental trends here are more dramatic in the model than in infants' performance, the model replicates the critical finding of an increase in the shift rate for the 10-month-olds on the three step test. This arises from a shift in WM across test trials. During the one step test, WM activity associated with the familiar item was relatively weaker (-.26) than during the three step test (.27). The increase in WM activity during the three step test enabled the model to quickly suppress activity associated with the familiar item and switch gaze to the novel item.

Individual Differences. In Chapter 4, I found that individual differences in looking were predictive of discrimination performance in infants and the model. This was quite remarkable, given that individual differences in the model were emergent, that is, there were not parameter manipulations that made some models exhibit more and less mature patterns of looking. Here, I used the DNF model to capture a wider array of looking measures than in Chapter 4, and I have captured them across three developmental time points during the first year. Recall that individual differences in looking indices of processing speed were predictive of discrimination on the one step test. To test whether the model exhibits the same pattern of results, I conducted the same regression analyses on the model data.

Table 11 shows results of the first analysis predicting the novelty score on the one step test. On the first step, age was entered as a predictor; on the second step, looking indices of processing speed were entered; and on the last step, looking time on the one step test was entered. As can be seen in the table, all predictors captured a significant proportion of variance. Critically, consistent with the empirical results, looking indices of processing speed accounted for a significant proportion of variance in novelty score on the one step test above and beyond the effects of age, change in R^2=.02. And consistent with results in Chapter 4, looking on the one step test continued to be a good predictor of performance on the one step test.

The regression results for the three step test are shown in Table 12. As in the infant analyses, none of the predictors captured a significant proportion of variance in three step test performance. Overall, individual differences in looking dynamics in the model were predictive of discrimination in ways comparable to analyses of infants' performance. As in Chapter 4, the proportion of variance in novelty scores accounted for by looking measures was comparable for infants and for the model. The DNF model, then, realistically captures the magnitude of the relationship between processing speed and discrimination.

Evaluating Model Fits. The DNF model captured developmental change in looking indices of processing speed and discrimination. The simulations also provided insights into the mechanisms that underlie looking dynamics across familiar and novel items that vary in their metric similarity. Visual inspection of the simulation results suggests that the DNF model was able to capture data from the familiarization and tests phases across development in some detail. To evaluate the fit of the model simulations to the infant data, I calculated the Root Mean Squared Error (RMSE) for means and standard deviations across all ages for four categories: looking time (total looking, looking on block one and block three, and peak look), shift rate (shift rate during familiarization, shift rate on one step test, shift rate three step test), duration (look duration familiarization, look duration one step test, look duration three step test), and novelty score (novelty score one step test, novelty score three step test). I also computed the RMSE for a second batch of 200 simulations at each age to ensure that the model produced replicable results. The results are shown in Table 13. Across all categories, the RMSE was comparable for the original simulations and the replication simulations. The model fit for means was good. The model produces a particularly good fit for novelty scores (.03). The model fit for standard deviations were also good, except for looking time (3.46). The model produced less variability in total looking than did infants.

Testing The Spatial Precision Hypothesis

The simulation results presented in the preceding section show that implementing the SPH in the DNF model can capture developmental changes in processing speed and discrimination in the VPC. This extends findings from Chapter 3 showing that implementing the SPH in the DNF model captured developmental changes in looking and discrimination in a single presentation task. There, however, I also found that increasing the strength of excitatory and inhibitory interactions within WM was sufficient to capture the developmental changes in performance, even when excitatory and inhibitory interactions within PF were relatively weak.

Here, I tested whether increases in the strength of neural interactions within WM were also sufficient to capture developmental change in looking and discrimination in the VPC. As in Chapter 3, I set self-excitation and inhibition within PF to the values to be weak, that is, to match the 5-month-old model and increased the strength of self-excitation in WM (c_{ww}) and the strength of the inhibitory connection from Inhib to WM (c_{wv}) to the values of the 7-month-old model in one set of simulations, and to the values of the 10-month-old model in a second set of simulations. There are two critical theoretical issues. First, does manipulating WM strength over development fit the data from Experiment 2 like the implementing the SPH does? The RMSE for these simulations are shown in Table 13 (see "5 Mo PF"). As can be seen, the RMSE is comparable to the original simulations in which the SPH was implemented for all measures except looking time. Implementing the SPH fit looking time much better than manipulating WM strength.

These results indicate that changes in neural interaction strength within PF make a contribution to the developmental profile. To probe the contribution of PF, I asked whether changes in the strength of WM were equally effective at fitting the infant data from Experiment 2 when the initial state of PF was stronger. I set the strength of PF to match the 7-month-old model. In one batch of simulations, I set WM strength to match the 5-month-old model, and in another batch of simulations, I set WM strength to match the 10-month-old model. The RMSE for these simulations are shown in Table 13 (see "7 Mo PF"). As can be seen, the RMSE is comparable to the simulations in which the initial state of PF was set to match the 5-month-old model: the simulations fit all measures well except looking time. In addition, when the initial state of PF was set to match the 7-month-old model, the model failed to capture developmental change in discrimination between 5 and 7 months of age. Figure 29 shows the novelty scores on the three step test for infants (left), the DNF model when the SPH was implemented (middle), and the DNF model when WM strength was manipulated with PF set to match the 7-month-old model (right). As can be seen in the figure, only implementing the SPH captured developmental change in discrimination.

In summary, regardless of whether PF was weak or strong, increasing the strength of WM alone did not fit the data from Experiment 2 as well as the SPH. When PF was strong, increasing the strength of WM alone did not capture developmental change in discrimination. These tests of the SPH suggest that changes in WM must be considered in the context of PF.

Discussion

Looking dynamics change dramatically across the first year of life. Changes in three looking measures have been studied extensively – shift rate, look duration, and peak look (Colombo & Mitchell, 1990; Rose et al., 2001; 2002; Ruff, 1975). With age, shift rate increases, look duration decreases, and peak look decreases. Developmental and individual differences in these looking dynamics are also associated with a decrease in exposure time to form a memory and recognize a stimulus. For this reason, these three looking measures have become well-known looking indices of processing speed. During the same developmental period that processing speed is changing, infants are also exhibiting an increased ability to make subtle discriminations along continuous dimensions. No previous study has investigated whether looking indices of processing speed and discrimination change together over development and are linked within individuals.

Experiment 2 showed that 7- and 10-month-olds, but not 5-month-olds, discriminated between dissimilar familiar and novel items on a continuous feature dimension, that is, older infants discriminated on the three step test. Experiment 2 also showed that look durations and peak looks became shorter between 5 and 7 months, and shift rate increased between 5 and 10 months of age. These findings indicate that discrimination and looking indices of processing speed change together over development at the group level of analysis. This supports the notion that processing speed and discrimination change together over development. The stronger claim of the DNF model, however, is that developmental changes in looking and discrimination *arise from the same mechanism*. The finding that looking indices of processing speed were predictive of novelty scores at test, that is, that individual differences in looking were linked to discrimination performance in both infants and the model, provides support for this claim.

One accomplishment of the DNF model is that it captures developmental change in looking and discrimination within the same architecture. Model simulations of the single presentation task showed that developmental change in looking and discrimination emerged from the same mechanism – changes in the strength of excitatory and inhibitory neural interactions. In this chapter, I addressed whether this same developmental mechanism can capture changes in looking and discrimination in the VPC. It was not immediately obvious that changes in the strength of neural interactions would capture performance in the VPC. Looking dynamics are considerably more complex – infants' looks are distributed across pairs of items, giving rise to measures such as shift rate not measurable in single presentation tasks. Moreover, discrimination is measured as a bias for one stimulus within a single trial instead of differential looking across two trials. The theoretical question, then, was whether changes in neural interaction strength are sufficiently general to capture developmental change in performance across tasks.

The simulation results showed that a simple mechanistic change specified by the SPH can capture developmental changes in looking indices of processing speed *and* discrimination. Moreover, tests of whether the SPH was required to capture these developmental changes suggest that increases in the strength of neural interactions in both PF and WM make a critical contribution to performance: model fits were improved when all four SPH parameters were changed, and the specific parameters for neural interactions in PF placed constraints on the qualitative pattern of discrimination performance over development.

The simulations of developmental change in looking in the single presentation task in Chapter 3 and the VPC here indicate that increases in the strength of neural interactions is a general developmental mechanism that spans multiple domains of cognition. I implemented the SPH in the very same way as Schutte and Spencer (2009) did to capture children's performance in spatial recall tasks and Simmering (2008) did to capture developmental changes in visual working memory. Thus, there appears to be continuity in these basic neural processes across development. There is also continuity in the consequences of the SPH on memory representations. In infants, stronger interactions lead to more stable and more precise memory representations, but memory representations are still less stable and less precise than in older children. For example, WM peaks during infancy only enter the self-sustaining state after prolonged exposure and rely on a strong contribution from a Hebbian process. WM peaks during childhood, by contrast, enter the self-sustaining state after relatively brief exposure to a stimulus and, therefore, rely less on Hebbian learning to enter this working memory state.

The DNF model also captured looking dynamics in impressive detail. At 10 months of age, for instance, the model produced an increase in shift rate from the one to the three step test. I showed that this behavior arises from a subtle shift in memory for the familiar item across the test phase. Moreover, as in Chapter 4, individual differences in looking during familiarization were related to differences in discrimination in a similar fashion in both models and infants. This suggests that individual differences need not reflect differences in the developmental state of each child; rather, some differences can emerge as initial differences in looking cascade over learning. Note that this does not imply that there are no stable characteristics of infants that influence looking. Indeed, there is good evidence that characteristics of the infant do stably influence looking. Infants born premature, for example, exhibit less mature patterns of looking and recognition performance than similarly aged term infants (Rose et al., 2001; 2002). In addition, individual differences in looking can be stable across ages (Colombo, Mitchell, O'Brien, & Horowitz, 187; Rose et al., 2001). Nevertheless, the present simulation and empirical findings demonstrate that an important direction for future research is to understand the joint influence of emergent and stable sources of individual differences.

Interestingly, individual differences in looking and discrimination were related somewhat differently across Chapters 4 and 5. In Experiment 1 (Chapter 4), looking on the one step test was predictive of discrimination on the one step test, and looking indices of processing speed were predictive of discrimination on the three step test. In Experiment 2 (Chapter 5), looking indices of processing speed were predictive of discrimination on the one step test. It is unclear what precisely contributed to this cross-study difference. The experiments did differ in two important ways. First, in Experiment 1, the order of the one and three step tests were counterbalanced across infants; in Experiment 2, however, the one step test was presented first for all infants. Second, in Experiment 1, only 10-month-olds participated; in Experiment 2, multiple age groups participated.

These cross-experiment differences could be probed experimentally. One could extend Experiment 2 by adding a sample of infants that experience the three step test first. Although this would make an important contribution, it would also be an expensive and lengthy task. An alternative is to run the experiment with an artificial sample of infants using the DNF model to gain some insight into the potential role of test order across development. The crucial issue is whether looking indices of processing speed are predictive of performance on the three step test across development when the order of test trials is counterbalanced. To address this issue, I ran the 5-, 7-, and 10-month-old model with the test order reversed. I then conducted hierarchical regressions to test whether looking indices of processing speed predict performance on the three step test and the one step test.

Table 14 shows the results for the one step test. As in Experiment 1, I entered looking indices of processing speed into the model first, followed by looking on the one step test second. The model was significant on both steps. I also asked whether order is related to novelty scores, and whether age is a significant predictor. Both predictors were statistically robust. Finally, I entered an age x order interaction term. The positive beta weight for the interaction term indicates that novelty scores on the one step test increase over development when the one step test is presented second.

Table 15 shows the regression results for the three step test. Interestingly, looking indices of processing speed were marginally predictive of novelty scores on the three step test. The interaction term—entered fifth—was also significant. The negative beta weight indicates that novelty scores on the three step test increase over development when the three step test is presented first. This indicates that, for the model, looking indices of processing speed are predictive on both the one step and three step test when the order of the one and three step tests are counterbalanced across individual simulations.

These simulations highlight one utility of a theoretical model. In particular, these simulations provide insight into the predictability of looking indices of processing speed under multiple task conditions. The simulations revealed that test order and age influence how looking is related to discrimination in complex ways. Testing these predictions will be an important goal for future empirical work.

In summary, the present chapter examined whether developmental change in looking indices of processing speed and discrimination change together over development. The empirical results showed that, indeed, shift rate, look duration, and peak look changed between 5 and 10 months, and these changes paralleled changes in discrimination. I also found that individual differences in looking indices of processing speed were linked to discrimination performance, which supports the conjecture derived from the DFT that looking and discrimination are linked mechanistically.

The SPH was able to capture developmental changes in looking and discrimination in the VPC. The simulation results presented here provide support for the hypothesis that increasing representational precision is a domain general developmental achievement. In particular, I captured developmental change in infants' discrimination abilities along a continuous feature dimension using the same mechanism that has been used to capture developmental change in the precision of children's working memory for spatial locations (Schutte & Spencer, 2009). The empirical results also provide support for this hypothesis. Interestingly, capturing developmental change in precision in the DNF model was an emergent property of neural interactions. Strong interactions between WM and PF enabled the model to recognize and detect novelty faster and more precisely over development.

In Chapter 6, I examine whether looking indices of processing speed and discrimination change together in at-risk infants. There is good evidence that looking indices of processing speed follow the same developmental trajectory across typically developing and atypically developing infant populations. However, how discrimination changes over development in at-risk infants has not previously been tested. Testing discrimination in at-risk infants will contribute to our understanding of how infant populations differ. This is an especially important issue because at-risk populations are often studied to gain insights into the meaning of individual differences.

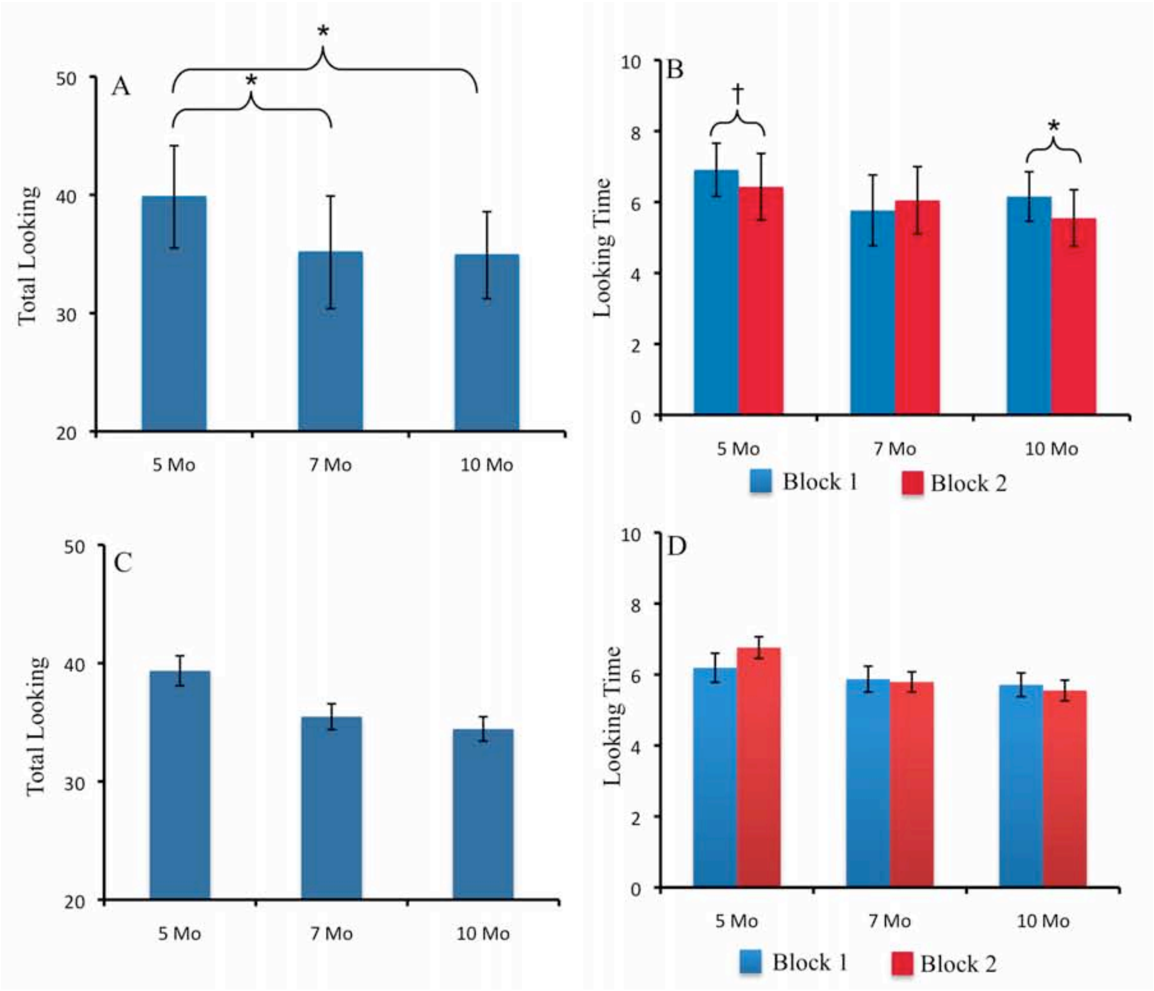
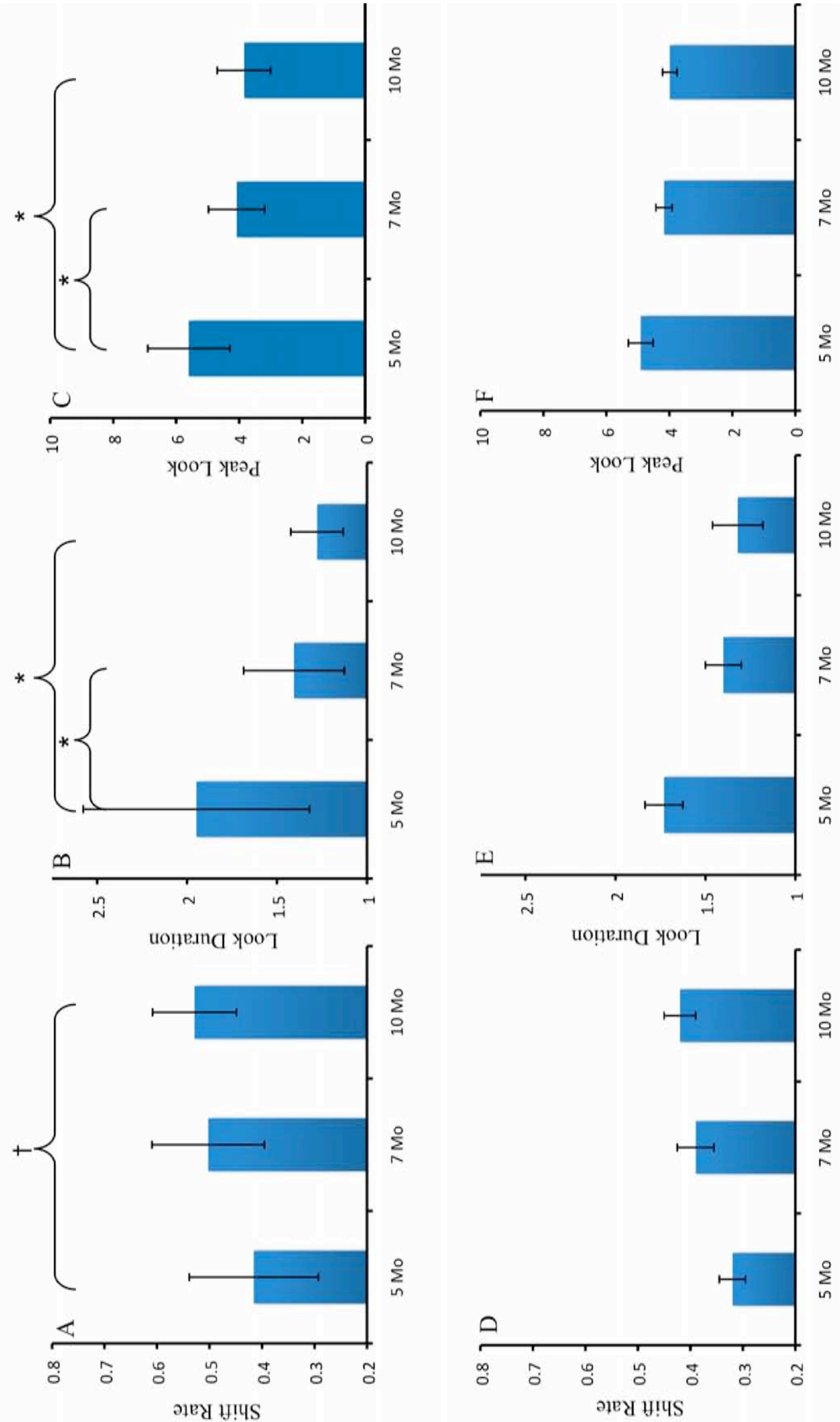


Figure 21. Looking Time Results for Infants and DNF Model. The top row shows infant data from Experiment 2. Mean total looking time across development (A) and looking time on the first and last block of two trials (B). The bottom row shows DNF model data. Mean total looking across familiarization (D) and looking time on the first block and last block (F). Error bars represent 1 SD. * significant post-hoc test. † marginally significant post-hoc test.

Figure 22. Processing Speed In Infants and Model. Panels A-C show infant data from Experiment 2. Mean shift rate (A), look duration (B), and peak look (C) for infants in Experiment 2. Panels D-F show the same data for the DNF model data. Mean shift rate (D), look duration (E), and peak look (F). Error bars represent 1 SD. * significant post-hoc test. † marginally significant post-hoc test.


A
Shift Rate
0.8
0.7
0.6
0.5
0.4
0.3
0.2
5 Mo
7 Mo
10 Mo
†
B
Look Duration
2.5
2
1.5
1
5 Mo
7 Mo
10 Mo
*
*
C
Peak Look
10
8
6
4
2
0
5 Mo
7 Mo
10 Mo
*
*
D
Shift Rate
0.8
0.7
0.6
0.5
0.4
0.3
0.2
5 Mo
7 Mo
10 Mo
E
Look Duration
2.5
2
1.5
1
5 Mo
7 Mo
10 Mo
F
Peak Look
10
8
6
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2
0
5 Mo
7 Mo
10 Mo

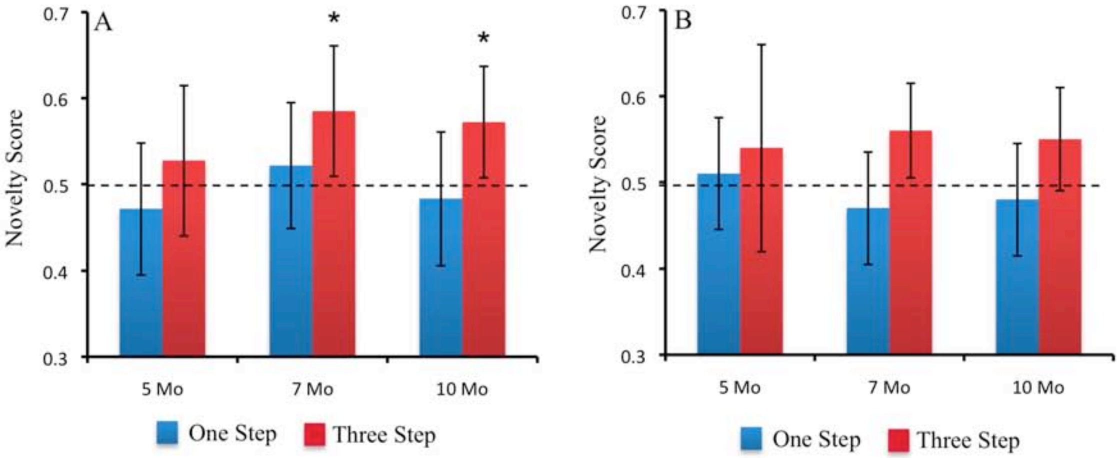


Figure 23. Discrimination In Infants and Model. (A) Novelty scores for infants on the one and three step tests from Experiment 2. (B) Novelty scores for the DNF model. Error bars are 1 SD. * significant one-sample t-test.

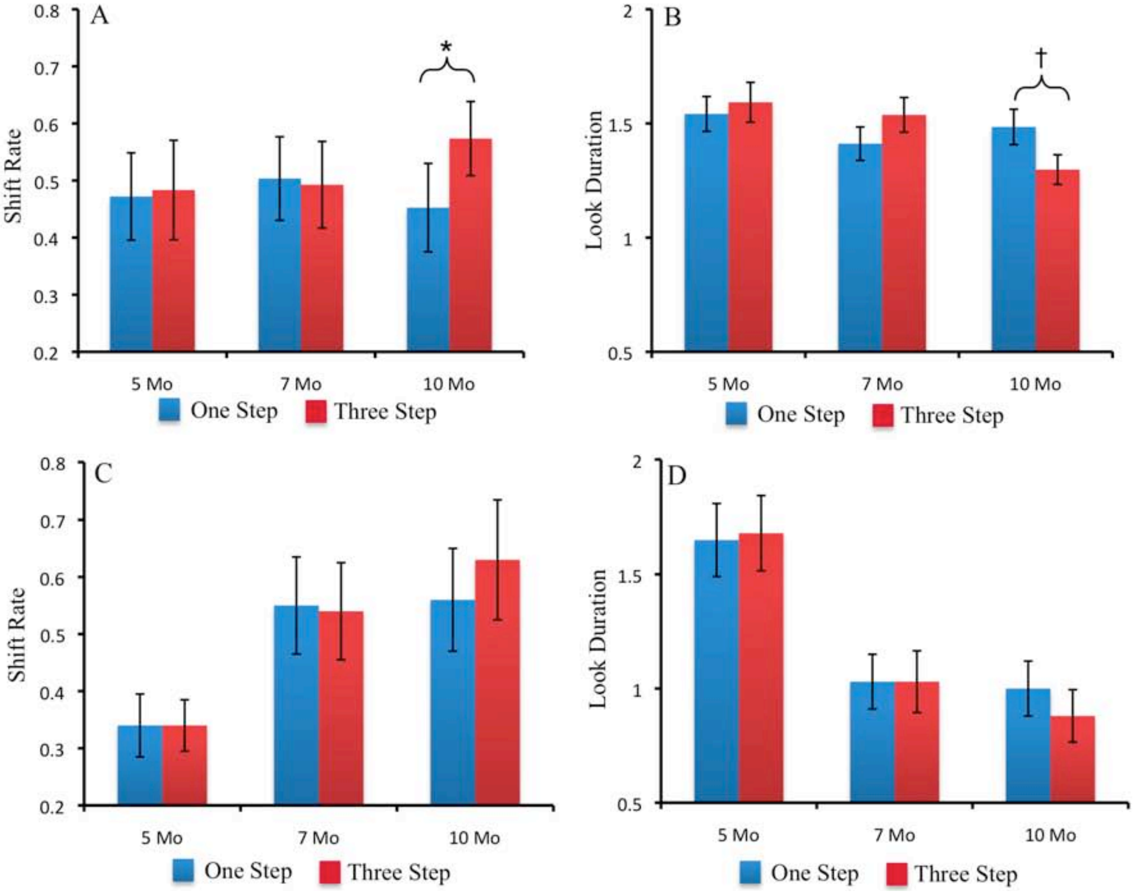
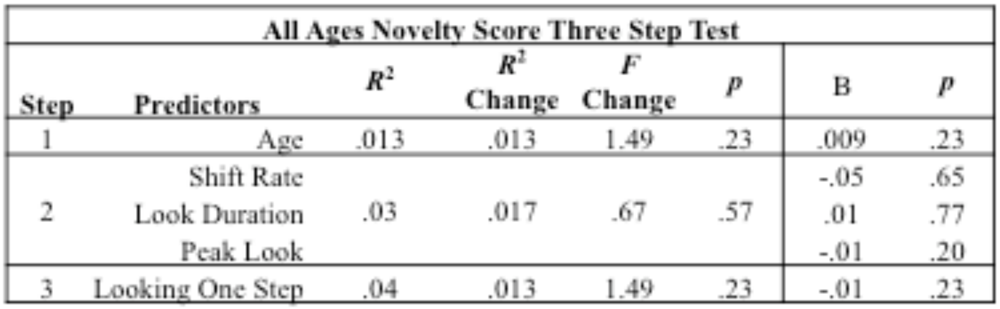


Figure 24. Looking Dynamics At Test In Infants and Model. Looking dynamics during test for infants in Experiment 2 (A-B) and DNF model (C-D). Mean shift rate on the one and three step tests (A,C) and mean look duration on the one and three step test (B,D). Error bars are 1 SD. * significant post-hoc test.

Table 8. Predicting One Step Novelty Score In Infants

All Ages Novelty Score One Step Test							
Step	**Predictors**	R^2	R^2 **Change**	F **Change**	p	B	p
1	Age	.001	.001	.08	.78	.002	.78
2	Shift Rate	.083	.083	3.42	.02	-.26	.01
	Look Duration					-.04	.14
	Peak Look					-.02	.05
3	Looking One Step	.087	.004	.51	.48	.003	.48

Table 9. Predicting Three Step Novelty Score In Infants



All Ages Novelty Score Three Step Test							
Step	**Predictors**	R^2	R^2 **Change**	F **Change**	p	B	p
1	Age	.013	.013	1.49	.23	.009	.23
2	Shift Rate	.03	.017	.67	.57	-.05	.65
	Look Duration					.01	.77
	Peak Look					-.01	.20
3	Looking One Step	.04	.013	1.49	.23	-.01	.23

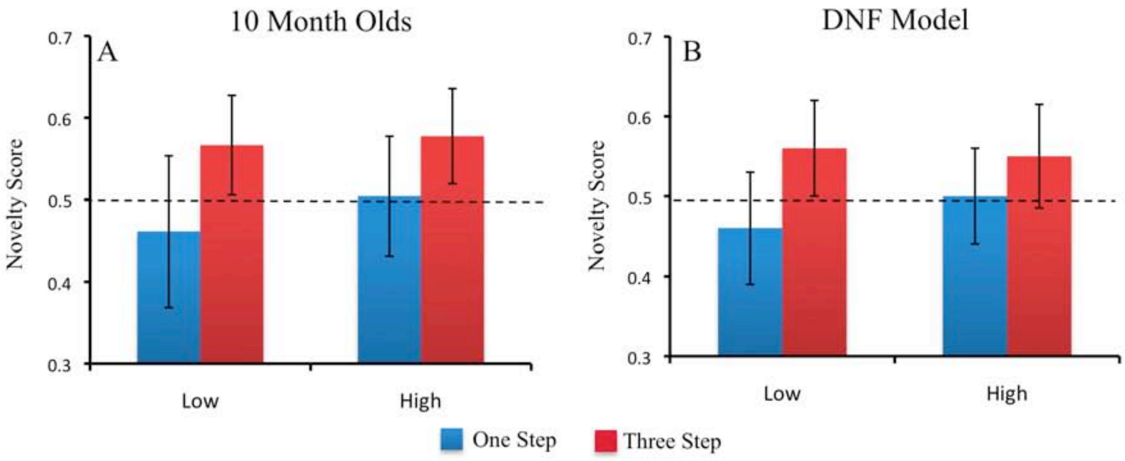


Figure 25. Cross-Parameter Stability. Novelty scores on one and three step test for 10-month-olds in Experiment 2 (A) and DNF model (B) when parsed into low and high looking groups as in Experiment 1.

Table 10. Developmental Model Parameters

PF(u)				WM(w)				Inhib(v)				Fixation(f)		Time Scales (τ)		Hebbian Learning (hl)	
	5 Mo	7 Mo	10 Mo		5 Mo	7 Mo	10 Mo		5 Mo	7 Mo	10 Mo	All Ages		All Ages		All Ages	
h_u	-10.20	-	-	h_w	-3.57	-	-	h_v	-10.20	-	-	c_{ci}	3.25	τ_{excite}	80	c_{hl}	2.40
c_{uu}	**0.1041**	**0.2082**	**0.3867**	c_{ww}	**0.7741**	**0.9676**	**0.9720**	c_{uv}	**1.1060**	**1.1642**	**1.4553**	c_{ff}	1.20	τ_{inhib}	10	σ_{uhl}	3.00
σ_{uu}	3.00	-	-	σ_{ww}	3.00	-	-	σ_{uv}	15.00	-	-	c_{fu}	0.35	τ_{build}	5000	c_{whl}	0.70
				c_{wu}	0.40	-	-	c_{vu}	0.80	-	-	c_{uf}	1.00	τ_{decay}	50000	σ_{whl}	3.00
				σ_{wu}	5.00	-	-	σ_{vu}	5.00	-	-	c_b	1.00				
				c_{vw}				c_{wv}	**0.1781**	**0.1875**	**0.2037**	c_{ag}	5.50				
				σ_{vw}				σ_{wv}	15.00	-	-	c_s	6.00				
								c_{vw}	3.00	-	-	c_{sa}	6.50				
								σ_{vw}	5.00	-	-	h_{rest}	5.00				
								k	0.1250	-	-	h_{down}	6.00				

Figure 26. Developmental Change In Processing Speed In DNF Model. Shows neural dynamics in DNF model underlying looking behavior during familiarization phase. Top row shows sum of PF activity while looking on each trial across the familiarization phase for the 5-month-old model (A), 7-month-old model (B), and 10-month-old (C) model. PF activity was stronger for the 5-month-old model than the 7- or 10-month-old models. Bottom row shows the state of PF and WM during the inter-stimulus interval after each familiarization trial, averaged across simulations. Neural interactions were weaker in the 5-month-old model (D), leading to stronger PF activity than in the 7- (E) and 10-month-old models (F) with stronger neural interactions. The stronger neural interactions of the older models gave rise to less total looking, higher shift rates, shorter look durations, and shorter peak looks relative to the weaker neural interactions in the younger model.

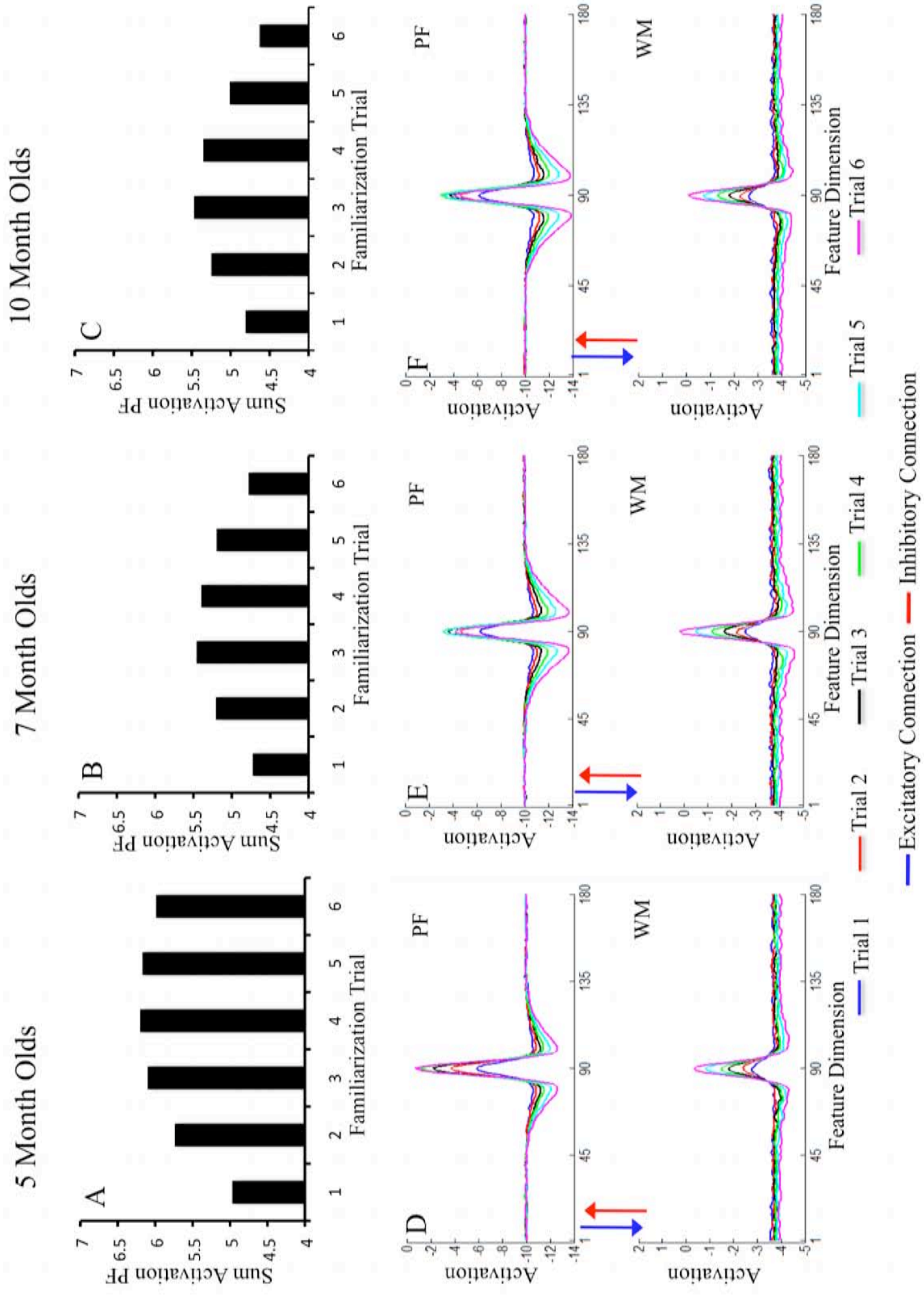

5 Month Olds
7 Month Olds
10 Month Olds
A
B
C
D
E
F
Sum Activation PF
Familiarization Trial
1
2
3
4
5
6
7
6.5
6
5.5
5
4.5
4
PF
WM
Activation
Feature Dimension
0
-2
-4
-6
-8
-10
-12
-14
2
1
0
-1
-2
-3
-4
-5
1
45
90
135
180
Trial 1
Trial 2
Trial 3
Trial 4
Trial 5
Trial 6
Excitatory Connection
Inhibitory Connection

Figure 27. Developmental Change In Discrimination In DNF Model. Shows neural dynamics in the DNF model that underlie developmental change in discrimination on the three step test. Top row shows the sum of PF activity while looking at the familiar item (black bars) and novel three step item (red bars) for the 5-month-old (A), 7-month-old (B), and 10-month-old (C) models. PF activity associated with the familiar item decreased over development. This led the older models to preferentially look at the novel relative to the familiar item. The bottom row shows the state of PF and WM while looking at the familiar item (black line) and novel three step item (red line). For the 5-month-old model, activation was comparable while looking at the familiar and novel item (D), leading to a null preference. For the 7-month-old (E) and 10-month-old (F) models, activation was stronger while looking at the novel item than while looking at the familiar item. This arises from suprathreshold activity associated with the familiar item in WM (see arrows), which produces strong inhibition in PF.

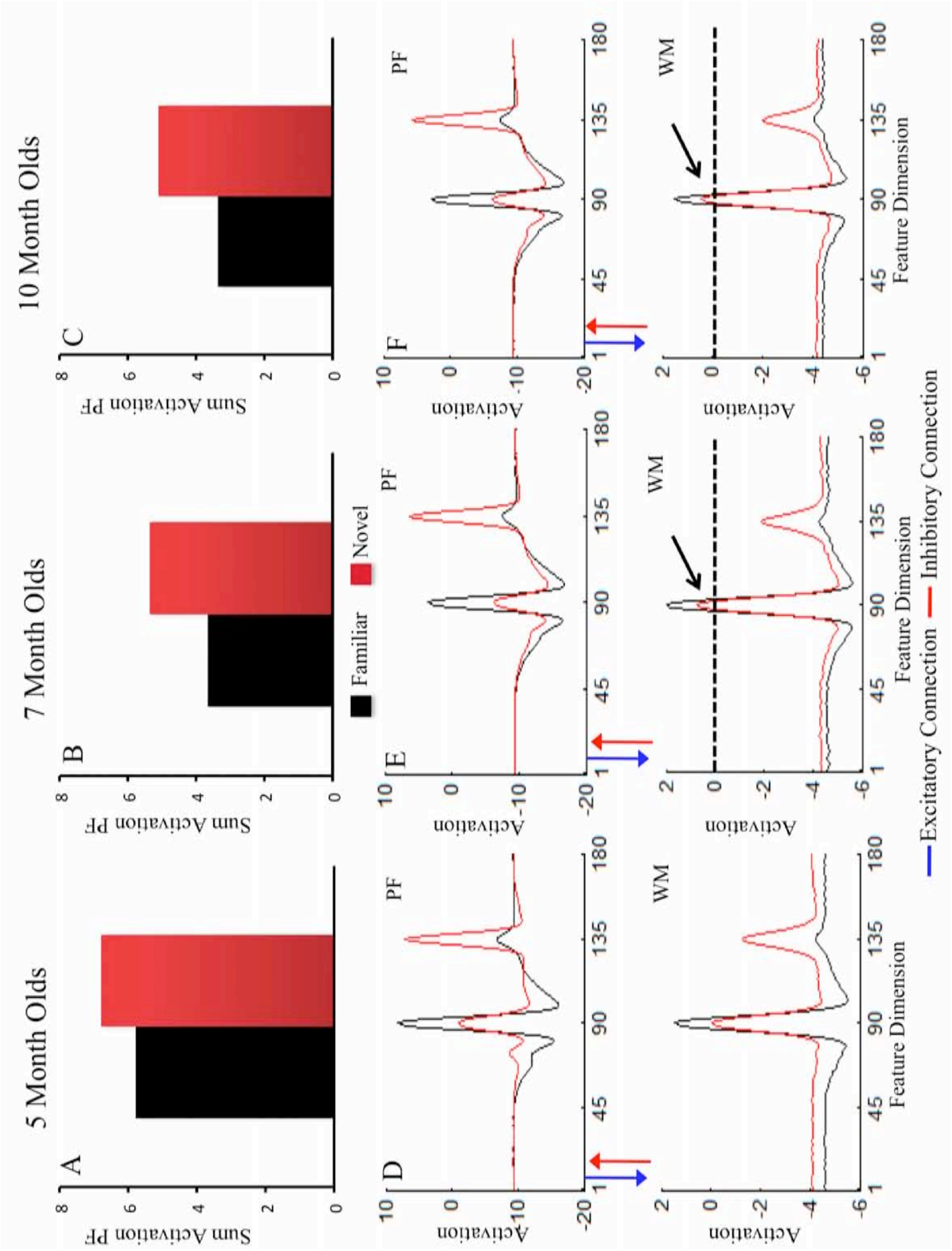

5 Month Olds
7 Month Olds
10 Month Olds
A
B
C
D
E
F
Sum Activation PF
8
6
4
2
0
■ Familiar
■ Novel
Activation
10
0
-10
-20
2
-2
-4
-6
PF
WM
1
45
90
135
180
Feature Dimension
— Excitatory Connection
— Inhibitory Connection

Figure 28. Fine-Grained Discrimination Across Development In DNF Model. Neural dynamics in the DNF model that underlie performance on the one test. Top row shows the sum of PF activity while looking at the familiar item (black bars) and novel one step item (red bars) for the 5-month-old (A), 7-month-old (B), and 10-month-old (C) models. PF activity associated with the familiar and novel item was comparable across development, leading to null preferences on the one step test for each model. The bottom row shows the state of PF and WM while looking at the familiar item (black line) and novel one step item (red line). Activation associated with the familiar and novel item were comparable for the 5-month-old (D), 7-month-old (E), and 10-month-old (F) models. However, in the older models activation associated with the familiar item was on the cusp of suprathreshold activity, which surfaced during the subsequent three step test trial.

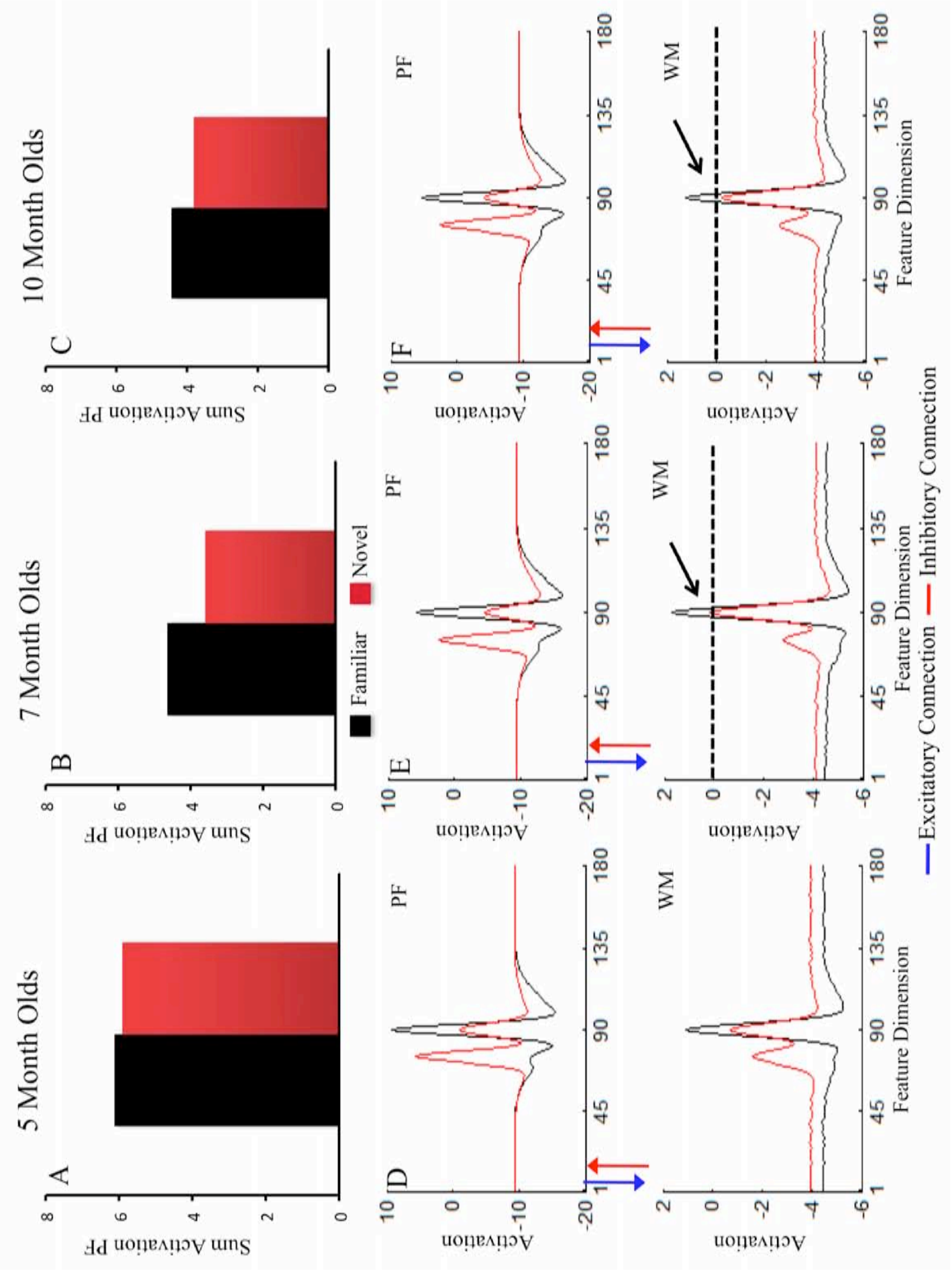

A
5 Month Olds
B
7 Month Olds
C
10 Month Olds
Sum Activation PF
8
6
4
2
0
Familiar
Novel
D
E
F
PF
WM
Activation
10
0
-10
-20
2
0
-2
-4
-6
1
45
90
135
180
Feature Dimension
Excitatory Connection
Inhibitory Connection

Table 11. Predicting One Step Novelty Score In Model

All Ages Novelty Score One Step Test							
Step	**Predictors**	***R^2***	***R^2* Change**	***F* Change**	***p***	B	***p***
1	Age	.007	.007	4.22	.04	-.005	.04
2	Shift Rate	.022	.015	2.98	.03	-.13	.20
	Look Duration					.04	.21
	Peak Look					.002	.83
3	Looking One Step	.069	.047	29.88	<.0001	.04	<.0001

Table 12. Predicting Three Step Novelty Score In Model

All Ages Novelty Score Three Step Test							
Step	**Predictors**	R^2	R^2 **Change**	F **Change**	p	B	p
1	Age	.001	.001	.51	.48	.002	.48
2	Shift Rate	.002	.001	.25	.86	-.05	.58
	Look Duration					-.01	.75
	Peak Look					.01	.58
3	Looking One Step	.004	.002	1.26	.26	-.01	.26

Table 13. Model Fits

	Looking Time		Shift Rate		Duration		Novelty Score	
Simulations	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Original	0.42	3.46	0.10	0.12	0.31	0.50	0.03	0.04
Replication	0.36	3.54	0.10	0.12	0.32	0.50	0.03	0.03
5 Mo PF	0.60	3.43	0.10	0.12	0.25	0.53	0.03	0.04
7 Mo PF	0.51	3.50	0.10	0.13	0.26	0.50	0.03	0.03

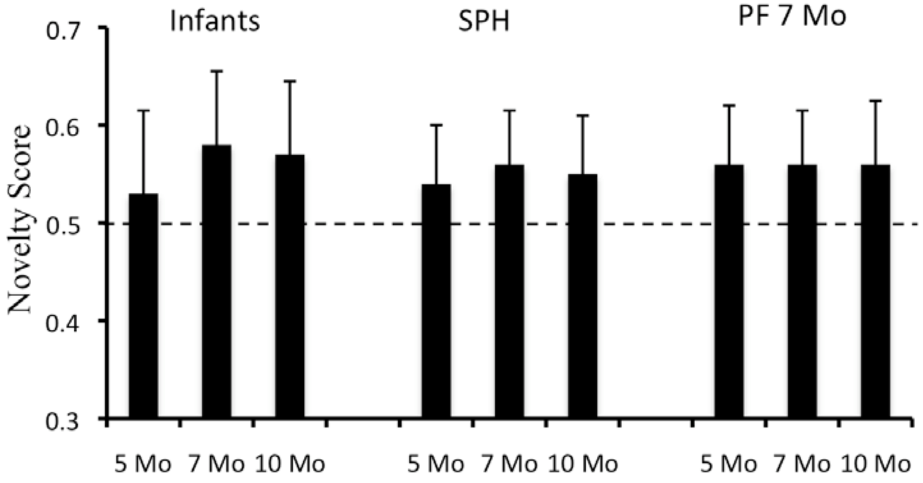


Figure 29. Novelty Scores For Tests of SPH. Novelty scores on three step test across development for infants in Experiment 2 (left), DNF model when the SPH was implemented in the model to capture developmental change (middle), and DNF model when PF was strong and WM strength was increased to capture developmental change (right).

Table 14. Predicting One Step Novelty Score in Model Test Order Reversed

All Ages Novelty Score One Step Test							
Step	**Predictors**	***R^2***	***R^2* Change**	***F* Change**	***p***	B	***p***
	Shift Rate					-.08	.23
1	Look Duration	.012	.012	4.75	<.01	.02	.28
	Peak Look					<.0001	.01
2	Looking One Step	.059	.047	59.63	<.0001	.03	<.0001
3	Age	.076	.017	22.55	<.0001	.01	<.0001
4	Order	.081	.004	5.79	<.05	.09	<.05
5	Age x Order	.085	.004	5.42	<.05	.01	<.05

Table 15. Predicting Three Step Novelty Score in Model Test Order Reversed

All Ages Novelty Score Three Step Test							
Step	**Predictors**	***R***^{2}	***R***^{2} **Change**	***F*** **Change**	***p***	B	***p***
1	Shift Rate	.005	.005	2.12	<.10	.01	.89
	Look Duration					.04	.07
	Peak Look					<.0001	.94
2	Looking One Step	.005	0	.02	.88	.001	.88
3	Age	.006	0	.24	.63	-.001	.63
4	Order	.008	.002	2.57	.11	.06	.11
5	Age x Order	.014	.006	7.45	<.01	-.01	<.01

CHAPTER 6

SPEED OF PROCESSING AND DISCRIMINATION IN AT-RISK INFANT POPULATIONS

The overarching goal of this thesis is to attain a deeper understanding of the link between looking and cognitive dynamics. One aspect of achieving this goal has been to develop a DNF model of infant looking and memory formation that overcomes limitations of previous models. A major accomplishment of the model was to capture developmental changes in discrimination and processing speed within the same system. This enabled me to evaluate whether these changes can arise from the same mechanism. Simulations of the DNF model showed that these developmental changes can, indeed, arise from the same mechanism—increases in the strength of neural interactions.

A fundamental assumption of DNFs is that stimuli are represented along continuous, metrically organized dimensions. Experiment 1 showed that infants, like the DNF model, can discriminate along a continuous feature dimension. Experiment 2 showed that developmental change in discrimination along a continuous feature dimension parallels changes in discrimination along continuous magnitude dimensions in visual and auditory domains, corroborating the notion that representational precision is a domain general developmental achievement. Experiment 2 also showed that looking indices of processing speed and discrimination change together over development, and that fine-grained discriminations and processing speed are linked within individuals. These findings, together, support the claim of the DFT that processing speed and discrimination change together over development and arise from the same mechanism.

Individual differences have also been studied in at-risk – most often preterm – infant populations. The motivation to study the looking behavior of preterm infants has largely been to test the processing speed hypothesis. The rational is that the adverse neonatal history of many premature infants should impact the neural processes underlying basic cognitive processes. The looking behavior of preterm infants generally resembles that of younger typically developing infants (Rose et al., 2001; 2002), which has been taken as additional evidence for the hypothesis that less mature patterns of looking within a sample of a given age reflect less mature cognitive processes.

Studying the looking behavior of preterm infants is also important clinically. Preterm infants are at risk for developmental delays in basic cognitive processes, special needs in the classroom, disabling conditions such as mental retardation, and diagnoses of childhood mental disorders such as Attention Deficit Disorder with Hyperactivity and Autism (Alyward, 2005; Biederman, Prince, Fischer, & Faraone, 2002; Larsson et al., 2005; Wilkerson, Volpe, Dean, & Titus, 2002). Studies on infant looking indicate that such delays are evident during infancy. If a rich enough understanding of the link between looking and cognitive dynamics can be attained, then looking might be successfully used as an early assessment tool. This, in turn, sets the stage for developing interventions that capitalize on the flexibility of the developing brain early in the first year. This is one long-term goal of this thesis.

In this chapter, I address three empirical questions surrounding the literature on the looking dynamics and recognition performance of at-risk infants that takes a first step toward this goal. The first question is whether looking indices of processing speed and discrimination follow the same developmental trajectory in at-risk infants as in typically developing infants. In the infant cognition literature, it is assumed that the processing speed of at-risk infants is delayed developmentally. This assumption has received some empirical support. Preterm infants generally exhibit looking dynamics and recognition performance that resembles younger, typically developing infants (Rose et al., 2001; for a review, see Rose et al., 2004; 2007). Importantly, the looking dynamics and recognition performance of preterm infants appears to follow the same developmental trajectory as typically developing infants: with age, preterm infants exhibit faster shift rates, shorter look durations, shorter peak looks, and stronger novelty scores. Upon closer inspection, however, typically developing and preterm infants do not always exhibit different behavioral patterns. Rose et al. (2002) found that typically developing and preterm infants differed in time to recognition at 5, 7, and 12 months of age but on looking indices of processing speed only at 12 months of age. In a serial recognition task, typically developing and preterm infants exhibited no differences in recognition performance (Rose et al., 2001b). An unresolved issue is why only some task conditions elicit population differences in performance.

A second question that this chapter tackles is whether population differences in looking indices of processing speed and discrimination are observed in the variant of the VPC used in Experiments 1 and 2. This variant differs from the VPC task used by Rose et al. (2001). In the VPC used here, infants are presented with a pair of identical items across 6 10 s trials. Looking dynamics such as shift rate are calculated across these trials. Discrimination is then tested on subsequent test trials and a single novelty score is obtained. In Rose et al's VPC, infants were familiarized with a stimulus and tested multiple times with different stimuli. For instance, an infant saw a face for 5 s and the infant's recognition of the face was tested. Then, the infant saw another face for 5 s and recognition was again assessed, and so on. In this context, looking dynamics such as shift rate were calculated across a series of familiarization trials with different stimuli. Although the two variants of the VPC share many commonalities, subtle differences might influence whether population differences are observed.

The third and last question this chapter addresses is centered on risk factors. Studies of preterm infants' looking and recognition performance often have an interest in whether or not risk factors are associated with performance. Evaluating associations between risk and performance is believed to provide insights into how an infant's neonatal history impacts real-time cognitive and behavioral dynamics. Such evaluations have lent support to the processing speed hypothesis – as described above, the rational is that adverse neonatal experience negatively impacts neurological development, measurable by looking indices of processing speed.

The link between risk and laboratory performance is not perfectly clear, however, because there is not a consistent pattern between risk factors and performance across studies (Sun, Mohay, & O'Callaghan, 2009; Rose et al., 2001; 2002). For example, in Rose et al's (2001) VPC, various measures of medical risk – presence of respiratory distress syndrome, days on respirator, days on oxygen, days in hospital, and APGAR scores – were related to various aspects of infants' performance. In Rose et al's (2002) processing speed task, by contrast, no risk factors were associated with performance. The picture is further complicated by changes in the factors that are related to various measures of performance across development. For instance, how many days infants are in the hospital may be associated with shift rate at 5 months of age but not 7 months. One approach to coping with this type of instability is to identify common factors that underlie multiple risk factors. For example, number of days on a ventilator, number of days on oxygen, and number of days in the hospital are often correlated and may be best described by an underlying “health” dimension. Here, I explore whether multiple risk factors can be reduced to a small number of common factors and whether these factors are associated with looking and recognition performance.

Experiment 3

Method

Participants. The final sample consisted of 66 infants. All infants were enrolled in the Iowa High-Risk Follow-up Program at the Children’s Hospital of Iowa at the University of Iowa Hospitals and Clinics. Seventy-seven percent of infants were born at or prior to 37 weeks gestation and admitted to the Neonatal Intensive Care Unit shortly after birth. However, some infants were enrolled in the program due to other risk factors surrounding the neonatal period and born after 37 weeks gestation. Infants in the high-risk program routinely visit the clinic at approximately 4, 8, and 12 months postnatal age; however, there was considerable variability in the age at which this sample of infants visited the clinic (e.g., many infants visit at 3, 5, 9 and 14 months postnatal age). All infants were recruited during their scheduled appointment to the clinic and tested at a convenient time during the visit.

The corrected age for each infant was calculated by subtracting the number of days each infant was born premature from the age at test. Infants were parsed into young and old groups based on a natural divide in corrected age near the median. The younger group consisted of 32 infants and was on average 4 months of age (*M*=111.94 days, *SD*=37.39). I will refer to this group as 4-month-olds. The older group consisted of 34 infants and was on average 10 months of age (*M*=289.56 days, *SD*=85.99). I will refer to this group as 10-month-olds.

Stimuli, design, and procedure. The stimuli, design, and procedure were identical to Experiment 2.

Results

I begin the results section with tests of looking measures during familiarization and test. After that, I investigate population differences in looking, individual differences in looking, and the relation between risk and looking.

Familiarization. Figure 30A-B shows two global characterizations of looking during the familiarization phase over development - mean total looking time (A) and looking on the first and last block (B). An unpaired t-tests revealed that 10-month-olds exhibited less total looking time than 4-month-olds, $t(64)=2.49$, $p<.05$. To examine whether looking across the first and last block changed over development, I conducted a repeated-measures ANOVA with block (first, last) as a within-subjects factor and age (4, 10) as a between-subjects factor. The test revealed a marginal main effect of block, $F(1,64)=2.91$, $p=.09$, and a marginal age x block interaction, $F(1,116)=3.56$, $p=.06$. Tests of simple effects revealed that 10-month-olds exhibited less looking on the last block than the first block, $F(1,64)=12.31$, $p<.001$, but 4-month-olds did not, $F(1,64)=1.21$, $p>.1$.

As with typically developing infants in Experiment 2, the primary analyses of looking dynamics focused on developmental change in three looking indices of processing speed – shift rate, look duration, and peak look (see Figure 31A-C). I evaluated developmental change in these looking measures using unpaired t-tests. Ten-month-olds exhibited a higher shift rate than 4-month-olds, *t*(64)=-2.56, *p*<.05, shorter look durations, *t*(64)=2.71, *p*<.01, and shorter peak looks, *t*(64)=3.30, *p*<.01. These changes suggest a robust increase in speed of processing over development in this sample of preterm infants.

Test. Infants' novelty scores on the one and three step tests are shown in Figure 32. To determine whether infants exhibited novelty scores that differ significantly from chance, I conducted a series of two-tailed, one-sample t-tests. On the one step test, the young group did not exhibit a reliable preference on the one step test, *t*(31)=-.98, *p*>.1, nor did the old group, *t*(33)=.49, p>.1. On the three step test, the young group exhibited a reliable novelty preference, *t*(31)=2.50, *p*<.05, but the old group did not, *t*(33)=.79, *p*>.1. These results indicated that young at-risk infants, but not relatively older infants, discriminate between dissimilar familiar and novel items. I also assessed whether there were any differences in test performance across development using a repeated measures ANOVA with test type (one step, three step) as a within-subject factor and age (4, 10) as a between-subjects factor. There were no significant effects.

As with typically developing infants in Chapter 5, I examined whether shift rate and look duration differed across the one and three step test over development (see Figure 33A-B). To evaluate shift rate, I conducted a repeated measures ANOVA with test (one step, three step) as a within-subject factor and age (4, 10) as a between-subjects factor. There was a significant main effect of age, *F*(1,64)=5.96, *p*<.05, indicating that 10-month-olds, overall, exhibited a higher shift rate during the test phase than 4-month-olds (see Figure 33A). I evaluated look duration during test using the same method. There was a main effect of age, *F*(1,64)=6.45, p<.05. Overall, the 4-month-olds exhibited longer look durations at test than did 10-month-olds. There was also a significant age x test interaction, *F*(1,64)=6.45, *p*<.05. Tests of simple effects revealed that 10-month-olds exhibited marginally shorter look durations on the three step test than the one step test, *F*(1,64)=3.28, *p*=.07, whereas 4-month-olds exhibited similar look durations across the one and three step tests, *F*(1,64)=2.33, *p*>.1.

Population Differences in Performance. One question this experiment seeks to answer is whether the variant of the VPC used here yields comparable population differences as the VPC used by Rose et al. (2001). This is an important question because cross-study differences in task and stimulus appear to influence whether or not population differences are observed. Recall that in Rose et al's VPC task, infants were familiarized with pairs of identical items on a single trial followed by a recognition test. These researchers found that 5-, 7-, and 12-month-olds differed on a number of looking measures and recognition performance. However, the measures on which infants differed were inconsistent across stimulus type (faces and patterns) and across ages. In Rose et al's (2002) processing speed task, infants were familiarized with pairs of different stimuli across trials – one that remained unchanged (familiar) and one that changed (novel). In this task, population differences were observed in the number of trials to recognize the familiar stimulus but few differences in looking dynamics were observed until 12 months of age. Note that examining whether variants of the VPC yield comparable population differences is also important for assessment purposes. If each task and stimulus context leads to different conclusions with respect to population differences, developing a general early assessment tool becomes a more difficult challenge.

I evaluated whether the VPC variant used here yielded similar results to Rose et al. (2001). Following Rose et al., I compared looking indices of processing speed from familiarization and comparable measures from test between similarly aged typically developing and at-risk infants. Across Experiments 2 and 3, the closest age matches were between 5- and 10-month-old typically developing infants and 4- and 10-month-old at-risk groups, respectively. I focused my analyses on the looking measures that were most comparable across the variant of the VPC used here and the VPC used by Rose et al. (2001).

Table 16 shows the results for the young group. Looking measures from familiarization are shown on the top and from test on the bottom. Shown on the right is whether or not Rose et al. (2001) observed population differences for faces or patterns. The results from the present study revealed significant differences between populations for shift rate and peak look during familiarization. Rose et al. also found differences on these measures, but observed a difference for look duration with patterns as well. During test, differences across populations were observed for shift rate and look duration on the one and three step tests. Rose et al. found differences on these measures for pattern stimuli as well. By contrast, these researchers reported a difference across populations for novelty scores with faces. In summary, analyses for the young group revealed a pattern of results that are, in many respects, comparable to results from Rose et al. (2001) with pattern stimuli.

Table 17 shows the same analyses for the old group. Results revealed cross-population differences on all three looking indices of processing speed during familiarization. Rose et al. (2001) found similar results for shift rate and look duration but not peak look. During test, no population differences were observed in the present study, whereas Rose et al. found differences for each measure either with faces or patterns.

Overall, the VPC used here yields comparable population differences during the familiarization and test phases early in development. Five of six population differences across familiarization and test phases observed by Rose et al. for patterns were also observed here. Later in development, population differences were comparable during the familiarization phase, but not during test. I return to a discussion of these data in the General Discussion.

Individual Differences. In Experiments 1 and 2, individual differences in looking indices of processing speed were predictive of discrimination performance within typically developing infants. One question is whether age and looking are related to discrimination in a similar way across infant populations. In other words, can the regression equation for typically developing infants also predict the novelty scores of at-risk infants? To probe this, I used the unstandardized beta weights from regressions from typically developing infants to generate a predicted novelty score. I then evaluated the correlation between the predicted and observed novelty scores for at-risk infants. I used the unstandardized beta weights from the last step in Table 11 for the one step test in which shift rate, look duration, and peak look accounted for a significant proportion of novelty score variability. The correlation coefficient was r=.08, p>.1. For the three step test, I used the unstandardized beta weights from the last step in Table 12, in which no measures accounted for a significant proportion of novelty score variability. The correlation coefficient was robust, r=-.25, p<.05, but the predicted novelty scores were in the opposite direction. This suggests that age and looking are related to discrimination across infant populations in different ways. To examine how age and looking are linked to discrimination in at-risk infants, I conducted the same hierarchical regressions for infants in Experiment 3 as for typically developing infants in Experiment 2.

In the first analysis, I examined how age and looking indices of processing speed were related to performance on the one step test. Results are shown in Table 18. Across the board, these regression analyses were consistent with Experiment 2. In particular, age did not account for a significant proportion of variance in novelty scores on this test trial. However, looking indices of processing speed captured a marginal proportion of variance above and beyond age, change in R^2=.10. Looking on the one step test was not a robust predictor. Inspection of the beta weights for the processing speed measures showed some differences relative to Experiment 2. For typically developing infants, shift rate was a strong predictor. For at-risk infants, look duration was a relatively strong predictor.

For the second analysis, I conducted the same regression but predicted performance on the three step test. Results are shown in Table 19. Age accounted for a marginally significant proportion of variance in novelty scores on this test, R^2=.04. Consistent with the group analyses, the negative beta weight indicates that novelty scores decreased with age. Additionally, looking indices of processing speed accounted for a significant proportion of variance in novelty scores on the three step test above and beyond age, change in R^2=.11. This is consistent with results of Experiment 1 with 10-month-olds, but not results of Experiment 2. Inspection of the beta weights indicates that look duration was the strongest predictor. Finally, looking on the one step test was not predictive of variance in three step test scores.

Overall, results of the regression analyses indicate that speed of processing and discrimination performance are, in fact, related in an at-risk population. The most robust predictor was look duration during familiarization. At-risk infants with shorter look durations showed higher novelty scores on the one and three step tests.

Risk Factors. The delayed performance of at-risk infants has generally been attributed to risk factors surrounding the neonatal period that are assumed to negatively impact the neural mechanisms underlying processing speed. The relationships between risk factors and looking measures have been assessed using correlations. Whether risk factors are correlated with looking measures has been inconsistent across studies, ages, and variables. In some studies, risk factors are correlated with looking and in other studies they are not; some risk factors are related to looking at one age but not at other ages; and some risk factors are related to one looking measure while other risk factors are related to another. This variation across studies makes interpretation difficult.

A different approach to exploring whether risk factors are related to looking measures is to characterize a collection of variables by an underlying dimension or factor. I used factor analysis to determine whether this was feasible. In particular, I used principle components analysis to determine whether common dimensions underlie subsets of the risk factors shown in Table 20. Inspection of a scree plot revealed that two components could be characterized by common factors. For the first factor, lower birth weight, prematurity, days in the hospital, days on a ventilator, days on oxygen, respiratory distress, and pulmonary distress were associated. I labeled this component "health." For the second factor, days spent on the ventilator and whether or not the mother smoked were associated. I labeled this component "parent-infant lung function."

Regression was used to obtain a unique score for each individual on each dimension/factor (i.e., health and parent-infant lung function). Using this score, I conducted a series of correlations with looking indices of processing speed as well as discrimination[1]. Results for looking measures during familiarization are shown in Table 21 and for test in Table 22. As can be seen, no looking measures were correlated with the health or parent-infant lung function dimensions duration familiarization. However, lung function showed a modest correlation with shift rate and look duration on the three step test.

Rose and colleagues have found that, *for the very same infants*, some task contexts yield population differences but no relations between risk factors and looking (Rose et al., 2001; 2002). The VPC used here did yield comparable population differences in looking relative to Rose et al. (2001). It is unclear, then, why the VPC used here did not capture relations between risk and looking. What is clear is that subtle task and stimulus differences can dramatically change whether population differences are observed and whether relations between risk factors and looking are observed. It is possible that some particular combinations of task conditions are more sensitive than others to this source of variance. It is also possible that risk factors have a complex and non-linear relationship to performance measured in laboratory tasks. It is notable that although these analyses did not reveal many robust relations between risk factors and looking, these relations were only evaluated within an at-risk sample of infants who are, as a group, impacted negatively by factors surrounding the neonatal period. These analyses do not indicate that health and parent-infant lung function have no impact on

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[1] There were no significant correlations between any risk factor alone and looking measures during familiarization or test.

looking, but rather, these analyses indicate that within an at-risk sample, variation on these dimensions does not strongly covary with looking.

Discussion

Experiment 3 addressed three questions. The first question was whether processing speed and discrimination along a continuous feature dimension follow the same developmental trajectory across typically developing and at-risk infant populations. In Experiment 3, measures of processing speed changed systematically over development, that is, looking indices of processing speed changed in a similar way as typically developing infants in Experiment 2. Moreover, regression analyses showed that looking indices of processing speed were related to discrimination performance. These results are consistent with previous studies showing that developmental change in at-risk infants' performance in memory tasks follows the same trajectory as typically developing infants (Sun et al., 2009; Rose et al., 2001; 2002). However, I did not find that older at-risk infants exhibit more mature discrimination performance than younger at-risk infants. I return to a discussion of this finding below.

Some studies have shown that at-risk infants exhibit behavior that resembles younger typically developing infants (e.g., Rose et al., 2001). Other studies, however, have reported no cross-population differences in performance. The second question addressed in Experiment 3 was whether the VPC variant used here yields population differences in looking indices of processing speed as the VPC variant used by Rose et al. (2001) does. This is an important question because, across studies, the stimulus and task context influences whether or not population differences are observed. Looking measures are a good candidate for assessing basic cognitive function in at-risk populations.

However, the task context must be sensitive to individual and population differences. Results generally showed that the VPC variant used here captures population differences in looking indices of processing speed, that is, at-risk infants exhibited looking dynamics that were less mature than similarly aged typically developing infants. One caveat is that the age range in the sample in Experiment 3 was more variable than in Experiment 2 and in other studies. An open question is whether the VPC variant used here continues to yield population differences in looking indices of processing speed with a more restricted age range for comparison.

The last question Experiment 3 addressed was whether common dimensions could be identified that characterize multiple risk factors. Previous studies have examined correlations between individual risk factors and looking, but results have been inconsistent. In some studies, risk factors are unrelated to looking. In other studies, risk factors are related to some looking measures but not others and, critically, whether risk factors are related to a given looking measure can change or even disappear over development. Moreover, interpreting individual risk factors and their relation to looking measures can be difficult. Here, I used factor analysis to determine whether common dimensions underlie multiple variables. Results showed that, indeed, health and parent-infant lung function dimensions could be used to characterize the risk of infants. Risk on these two dimensions, however, was not generally related to looking indices of processing speed, suggesting that the VPC variant used here was not sensitive to the contribution of these factors to performance or, alternatively, that these risk factors have a complex relationship to behavioral performance in laboratory tasks.

Infants' scores on the parent-infant lung function dimension were marginally correlated to shift rate and look duration on the three step test. Although this correlation is difficult to interpret, it is interesting that a relation to these particular looking dynamics was observed. Recall that in Chapter 5, the 10-month-old model exhibited a high shift rate and short look durations on the three step test relative to the one step test. These dynamics emerged from an increase in memory across the test phase. It is possible that the relations between risk and these looking measures reflect something about these underlying memory dynamics. This suggests that the DNF model might be a useful tool for understanding how risk factors impact cognitive dynamics.

The results of Experiment 3 were generally consistent with previous studies. There were similar changes in looking over development in at-risk infants as typically developing infants, for example, and at-risk infants exhibited less mature patterns of looking that similarly aged typically developing infants. However, I also observed here that at-risk infants' discrimination does not appear to follow the same trajectory as typically developing infants. Interestingly, I found that the discrimination of young at-risk infants resembles that of older typically developing infants, whereas the discrimination of older at-risk infants resembles that of younger typically developing infants. In particular, 4-month-old at-risk infants exhibited evidence of discrimination on the three step test, but 10-month-old at-risk infants did not. An open empirical question is whether even older at-risk infants would exhibit discrimination on the three step test, that is, is the developmental trajectory of discrimination u-shaped for at-risk infants?

It is notable that there was considerable variability in age within the 4- and 10-month-old samples. One direction for future research will be to examine how discrimination changes over development when age is more tightly constrained. Nevertheless, Experiment 3 suggests that young at-risk infants discriminate between dissimilar familiar and novel items but older at-risk infants do not? Although speculative, one possible reason for this finding is that the immature looking dynamics of at-risk infants actually facilitates memory formation. Four-month-old at-risk infants exhibited longer peak looks and slower shift rates than similarly aged typically developing infants. Long peak looks and few gaze switches may facilitate memory formation. As infants' peak looks become shorter and they switch gaze more with age, memory formation may be hampered. This possibility is not consistent with the processing speed framework where speed is hypothesized to increase with development. This leads to improved recognition. Here, I found that looking changes over development in a manner that is consistent with notion that processing speed is increasing over development. However, the poorer recognition of older infants is inconsistent with this notion. Within a dynamic systems framework, this possibility does make sense - the dynamics of one system – in this case, the fixation system – can influence the dynamics of another – in this case, processing. By this view, memory formation, an inherently time-dependent process, may actually be enhanced in a young infant with underdeveloped fixation dynamics.

In Chapters 3 and 5, I captured developmental change in looking in the DNF model by manipulating the neural dynamics that govern perceptual and memory dynamics. Clearly, developmental changes in memory formation can influence the temporal dynamics of looks, as in the DNF model. However, changes in looking dynamics might also influence memory formation. To capture the looking and discrimination performance of 6- to 12-week-old infants in a single presentation task, Perone and Spencer (2010) implemented the SPH on the fixation system of the DNF model to increase the length of fixation durations.

There are pronounced changes in gaze shifting early in development that may influence memory formation in young infants. In particular, Robertson et al., (2001) measured the body movements of 1- and 3-month-olds while they looked at an array of toys and found that periods of body movement preceded shifts of gaze and returned to baseline after the onset of fixation. Interestingly, the body movements of 1-month-olds were protracted relative to 3-month-olds, slowing shifts of gaze. Slowed gaze shifting maintains fixation on a particular stimulus. Moreover, 1-month-olds make several slow saccades when shifting gaze, whereas 2- and 3-month-olds make relatively fewer and faster saccades when shifting gaze (for a review, see Johnson, 2002). These changes in fixation dynamics might occur independently of changes in memory dynamics. Inspection of Tables 16 and 17 show that typically developing and at-risk infants differ on looking measures but not recognition measures. This might indicate that typically developing and at-risk infants primarily differ in occulomotor control.

Although slow gaze shifting is viewed as a sign of slow processing (e.g., Rose et al., 2002), slow gaze shifting might actually facilitate memory formation. Indeed, Perone and Spencer (2010) showed that manipulating fixation dynamics in the DNF model such that look durations were prolonged facilitated memory formation, while short look durationshampered memory formation. The rate of gaze shifting might also influence the contribution that novel items can make to the maintenance of fixation. When the fixation system in the DNF is tuned such that it tends to frequently switch gaze, the response of a novel item has to be quite strong to sustain fixation. In this thesis, I only manipulated four developmental parameters that influence the strength of neural interactions in a perceptual and working memory field. These changes were sufficient to capture developmental change in looking dynamics and discrimination between 5 and 10 months. Nevertheless, there are dramatic improvements in motor sources of gaze shifting during this period. Consistent with this, Perone and Spencer (2010) found that changes in the fixation system of the DNF model were required to capture learning in infants between 1 and 4 months of age. This suggests that an exciting direction for future research is to examine the trajectory along which fixation and memory dynamics change over development and influence the interaction between looking and cognition.

In summary, looking indices of processing speed develop along the same trajectory across at-risk and typically developing infant populations. This is consistent with previous studies showing the same cross-population developmental pattern (Rose et al., 2001). Interestingly, discrimination does not appear to develop along the same trajectory as with typically developing infants. Young at-risk infants discriminate between dissimilar familiar and novel items, but older at-risk infants do not. The looking dynamics of young at-risk infants appear to be less developmentally advanced than similarly aged typically developing infants. It is possible that the less mature looking dynamics of young at-risk infants facilitates memory formation and/or novelty detection. The findings reported here add to our understanding of how infant populations differ. However, they also show that developmental change in looking and discrimination can be linked in complex ways. This suggests that a promising direction for future work would be to use computational models like the DNF model to try to understand how patterns of performance change both across tasks and across development.

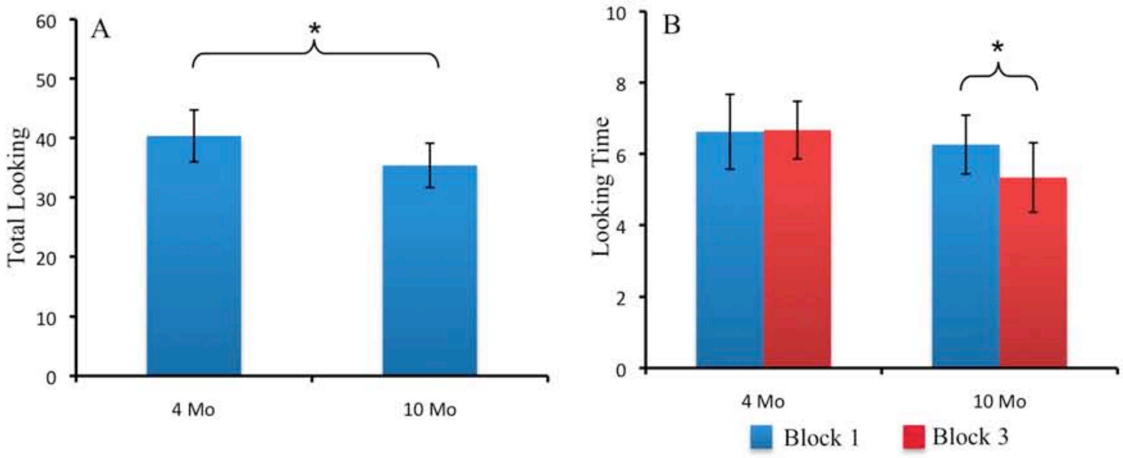


Figure 30. Looking Time In At-Risk Infants. Shows looking time accumulated across familiarization (A) and looking time during the first and last block (C) for at-risk infants in Experiment 3. Error bars represent 1 SD. * statistically significant for total looking; post-hoc significant for looking time across blocks.

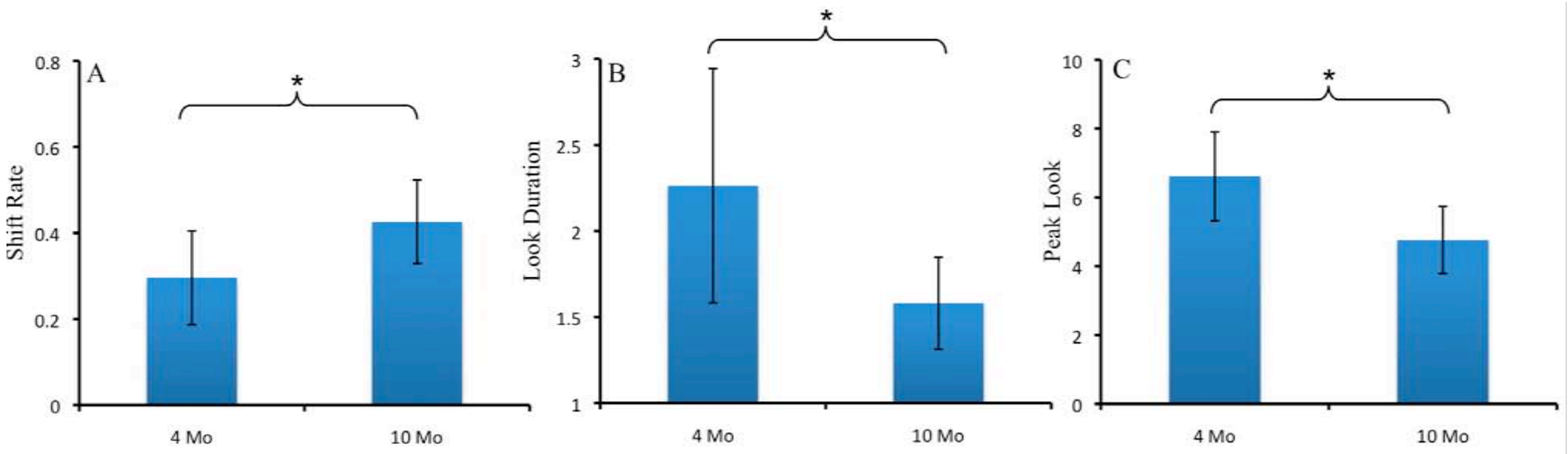


Figure 31. Processing Speed In At-Risk Infants. Mean shift rate (A), look duration (B), and peak look (C) for at-risk infants in Experiment 3. Error bars represent 1 SD.* statistically significant.

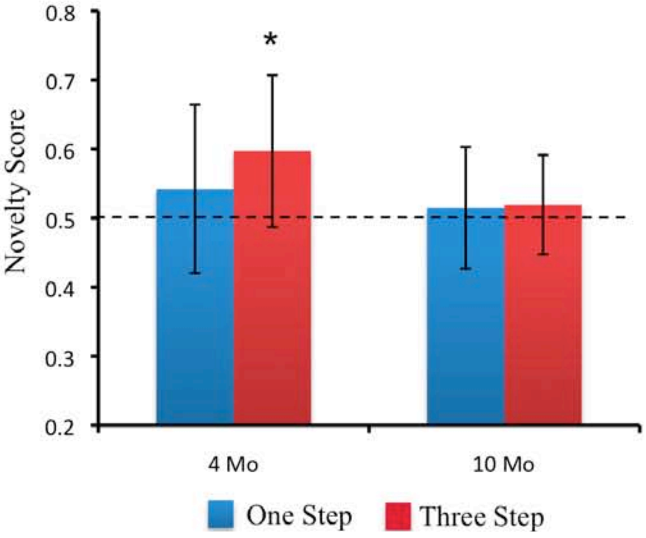


Figure 32. Discrimination In At-Risk Infants. Novelty scores for at-risk infants in Experiment 3. Error bars represent 1 SD. * significant one-sample t-test

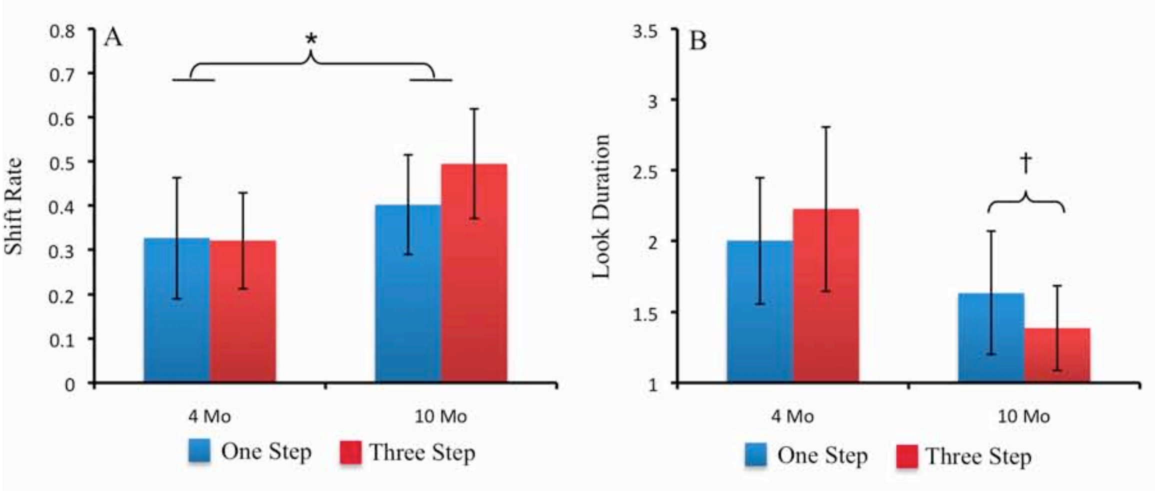


Figure 33. Looking Dynamics At Test For At-Risk Infants. Mean shift rate on the one and three step test (A) and mean look duration on the one and three step test (B) for at-risk infants in Experiment 3. Error bars represent 1 SD. * statistically significant; † marginal post-hoc test.

Table 16. Comparisons For Young At-Risk and Typically Developing Infants

	Experiments 2 & 3				Rose et al. (2001)	
	5 Mo Olds	4 Mo Old At Risk	*t*(1,75)		5 Mo Olds Faces	5 Mo Olds Patterns
	Familiarization					
Shift Rate	0.42	0.3	-2.21	*	Yes	Yes
Look Duration	1.95	2.26	1.05		No	Yes
Peak Look	5.6	6.61	1.69	†	Yes	No
	Test					
Novelty Score One Step	0.47	0.54	1.57		Yes	No
Shift Rate One Step	0.47	0.33	-2.34	*	No	Yes
Look Duration One Step	1.54	2	2.47	*	No	Yes
Novelty Score Three Step	0.53	0.6	1.55		Yes	No
Shift Rate Three Step	0.48	0.33	-3.24	**	No	Yes
Look Duration Three Step	1.59	2.23	2.73	**	No	Yes

†<.1 *<.05 **<.01

Table 17. Comparisons For Old At-Risk and Typically Developing Infants

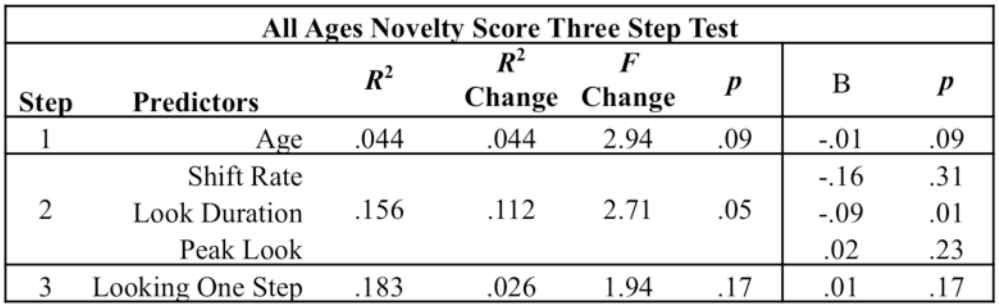
	Experiments 2 & 3				Rose et al. (2001)	
	10 Mo Olds	10 Mo Old At Risk	*t*(1,67)		12 Mo Olds	
					Faces	Patterns
	Familiarization					
Shift Rate	0.53	0.43	-2.39	*	Yes	Yes
Look Duration	1.28	1.58	2.92	**	Yes	Yes
Peak Look	3.85	4.76	2.07	*	No	No
	Test					
Novelty Score One Step	0.48	0.51	0.79		No	Yes
Shift Rate One Step	0.45	0.4	-1		Yes	Yes
Look Duration One Step	1.48	1.63	0.84		Yes	Yes
Novelty Score Three Step	0.57	0.52	-1.6		No	Yes
Shift Rate Three Step	0.57	0.48	-1.37		Yes	Yes
Look Duration Three Step	1.3	1.39	0.63		Yes	Yes

†<.1 *<.05 **<.01

Table 18. Predicting One Step Novelty Score In At-Risk Infants

All Ages Novelty Score One Step Test							
Step	**Predictors**	R^2	R^2 **Change**	F **Change**	p	B	p
1	Age	.010	.010	.67	.42	-.01	.42
2	Shift Rate	.109	.098	2.24	.09	.16	.37
	Look Duration					-.07	.08
	Peak Look					.02	.23
3	Looking One Step	.110	.001	.10	.76	-.002	.76

Table 19. Predicting Three Step Novelty Score In At-Risk Infants



All Ages Novelty Score Three Step Test							
Step	**Predictors**	***R^2***	***R^2* Change**	***F* Change**	***p***	B	***p***
1	Age	.044	.044	2.94	.09	-.01	.09
2	Shift Rate	.156	.112	2.71	.05	-.16	.31
	Look Duration					-.09	.01
	Peak Look					.02	.23
3	Looking One Step	.183	.026	1.94	.17	.01	.17

Table 20. List of Risk Factors

Risk Factors
Birthweight
Gestational Age
Size For Gestational Age
1 minute APGAR
5 minute APGAR
Days on Ventilator
Days on Oxygen
Days in Hospital
Respiratory Distress Syndrome
Bronchopulmonary Dysplasia
Mothers Age
Mother Smoking

Table 21. Correlations Between Risk and Processing Speed

	Familiarization		
	Shift Rate	Look Duration	Peak Look
Health	-0.16	0.08	0.1
Lung Function	-0.11	0.14	0.03

†<.1

Table 22. Correlations Between Risk and Discrimination

	One Step Test			Three Step Test		
	Novelty Score	Shift Rate	Look Duration	Novelty Score	Shift Rate	Look Duration
Health	-0.1	-0.04	-0.05	-0.06	0.02	0.07
Lung Function	0.02	0.07	-0.03	0.08	0.22†	-.23 †

†<.1

GENERAL DISCUSSION

The overarching goal of this thesis was to gain a richer understanding of the link between looking and cognitive dynamics. During the past half-century, our understanding of the origins of cognition has grown immensely. This growth is largely attributable to the use of looking measures to study basic cognitive processes. Looking measures have enabled researchers to study developmental change in attention (Ruff, 1975), speech (Saffran et al., 1996), visual perception (Johnson, 1996), visual categorization (Oakes et al., 1997), working memory for colors (Ross-Sheehy et al., 2003) and locations (Oakes, Ross-Sheehy, & Luck, 2006), cross-modal processing (Bahrick, 2001), and word learning (Werker et al., 1998). Looking measures have also stirred controversy (for reviews, see Haith, 1998; Spelke, 1998). Historically, many debates within the field of infant cognition have been centered on various interpretations of looking measures. A better understanding of the link between looking and cognition could help resolve such debates (see Schöner & Thelen, 2006).

Looking is a powerful empirical tool, but it is also an active behavior by which infants explore their world, acquire knowledge, and interact with social partners. The accumulation of such interactions can have a profound positive impact on the social and cognitive development of at-risk infants (Landry et al., 2008). A better understanding of the active nature of looking could help develop interventions in which social partners play on looking to gain access to and alter cognitive dynamics in atypically developing children.

To attain a richer understanding of the link between looking and cognitive dynamics, I proposed a dynamic field theory of infant looking and memory in Chapter 3 and formalized the theory in a DNF model. The DNF model was able to overcome three limitations of existing models. One limitation is that existing models have not captured non-linear changes in memory and looking (Colombo et al., 1990; Roder et al., 2000). The DNF model overcame this limitation via the non-linear transition into the working memory state that occurs during learning. Simulations showed that this leads to an associated non-linear decline in looking when simulations were aligned on the trial of working memory formation.

A second limitation of existing models is that they have not captured the active, exploratory nature of looking. Instead, they treat looking as a behavioral output of cognitive processing. How infants distribute their looks, however, is intertwined with memory formation (Jankowski et al., 2001). The distribution of looks in the DNF model is also intertwined with memory formation – fast processing simulations exhibit fewer looks, longer look durations, and more looking time early in learning than slow processing simulations.

The last limitation of existing models is that they have not captured developmental change in looking indices of processing speed and discrimination within a single system and, therefore, have not specified whether these changes can arise from the same or a different mechanism. I generalized the Spatial Precision Hypothesis (SPH) from the domain of spatial cognitive development (Schutte et al., 2003; Schutte & Spencer, 2009) to the domain of infant looking and memory, which posits that the strength of excitatory and inhibitory interactions increase over development. Remarkably, these same changes in neural interactions that capture children's performance in spatial recall tasks captured developmental change in looking indices of processing speed, the time course of working memory formation, and discrimination. I was able to show, then, that these changes can arise from the same mechanism over development.

In Chapter 4, I generalized the DNF model from the single presentation task context to the VPC by expanding the fixation system to explore multiple locations. The VPC allows infants to explore objects at multiple locations, and in this way is a more ecologically valid task context. I showed that the generalized model could capture the richer set of looking dynamics measurable in the VPC, such as shift rate, without any modification to the principles that govern the perceptual, memory, and fixation system in the DNF model.

The generalized DNF model is a dynamic, autonomous exploratory system. A signature of exploratory systems is familiarity and novelty seeking. It has long been assumed that familiarity biases are driven by initial encoding of new items, and novelty biases are driven by robust memory for familiar items. Indeed, all theories of infant habituation posit that familiarity biases arise prior to novelty biases (Hunter & Ames, 1988; Sirois & Mareschal, 2004). Whether adults exhibit a familiarity or novelty bias, however, depends on the task (Dodd et al., 2009) and stimulus context (Park et al., 2010). This is the case even when memory for familiar items is robust.

The conditions under which familiarity and novelty biases arise is a particularly salient issue in the infant cognition literature. Many debates have been centered on whether a given preference is a familiarity or novelty preference, the choice of which can sometimes radically change the conclusions drawn from a study (see Cashon & Cohen, 2000). Recent evidence indicates that robust memory can lead to familiarity bias when the task context is a demanding one (Shinskey & Munakata, 2005). Consistent with this finding, in Chapter 4 I tested and confirmed a prediction of the DNF model that familiarity biases can arise from a robust memory when familiar and novel items are highly similar, that is, in a demanding stimulus context.

More specifically, the model predicted that the same robust memory late in learning induces a familiarity bias when familiar and novel items are similar and a novelty bias when familiar and novel items are dissimilar. In the most radical case, the model predicted a novelty-to-familiarity shift across test trials. Additionally, analyses of the model's looking and neural dynamics showed that low levels of looking across similar familiar and novel items (one step test) were associated with stronger working memory and familiarity preferences. When simulations were split into low and high looking groups based on a median split of looking time on the one step test, only low looking simulations exhibited a familiarity bias on the one step test and a novelty bias on the three step test. All of these predictions were confirmed experimentally with 10-month-old infants. Indeed, the fit of the model to infants' performance was robust even at the level of individual differences. In particular, regression analyses showed similar patterns of covariance across the model and infant samples.

There were three additional accomplishments of Chapter 4. First, the empirical results showed that 10-month-olds can discriminate along a single, continuous metrically organized feature dimension embedded in a multi-dimensional object. Previous studies have shown that infants can discriminate between stimuli that differ in the number of dimensions (Welch, 1974), along both dimensions of a two-dimensional object (Cohen et al., 1971), and along continuous, metrically organized magnitude dimension such as area (Brannon et al., 2006). No previous study has tested discrimination on a single, continuous feature dimension, in part, because few stimulus sets have well-controlled metric properties. Second, model simulations and empirical results showed that individual differences in looking were related to discrimination. In particular, looking on the one step test was related to discrimination on the one step test. And well-known looking indices of processing speed – shift rate, look duration, and peak look – during familiarization were related to performance on the three step test. Lastly, the empirical results show that the DNF model is able to capture—and predict—meaningful links between looking and memory formation in infants. This motivated the next study probing changes in looking and cognitive dynamics over development.

Chapter 5 asked whether looking indices of processing speed and discrimination change together over development and are linked within individuals. Previous studies have shown that shift rate increases, look duration decreases, and peak looks decrease over development; however, it is unclear how these changes are related to changes in discrimination over the first year. To address this question, I measured looking indices of processing speed and discrimination performance in 5-, 7-, and 10-month-olds. Results showed that looking indices of processing speed and discrimination change together over development. Consistent with previous studies, infants exhibited faster shift rates, shorter look durations, and shorter peak looks with age. Infants also discriminated between familiar and dissimilar items at 7 and 10 months but not 5 months of age. Finally, individual differences in looking indices of processing speed were linked to discrimination in the regression analyses. Interestingly, looking measures were linked to discrimination on the one step test, but not the three step test as in Chapter 4.

These data are consistent with simulation results of the DNF model showing that developmental changes in looking and discrimination can arise from the same mechanism. In Chapter 5, I also tested whether the SPH could capture developmental change in looking dynamics and discrimination in the VPC. Simulation results showed that, indeed, the SPH captured these developmental changes: the model captured data from 36 mean values and 36 standard deviation measures by scaling 4 model parameters systematically over development. I also tested whether the SPH was *required* to capture these changes. Although scaling of the strength of neural interactions in working memory did yield a satisfactory fit for many measures of performance, changes in working memory alone did not effectively capture changes in looking time over development. Moreover, simulations of the model that were initialized with 7-month-old parameter values did not capture the qualitative pattern of results over development. In particular, the model failed to capture the improvement in discrimination between 5 and 7 months. Thus, changes in both PF and WM parameters are needed to capture the entire profile of developmental change.

Critically, individual differences in looking during familiarization were related to differences in discrimination in the model and infants, despite the fact that all model simulations within a given age were run with the exact same parameters. Thus, stochastic fluctuation in the DNF model captured the link between individual differences in looking and discrimination. This finding may indicate that some individual differences in the literature may have a stochastic source and emerge as infants look and learn. Although such differences emerge through initial fluctuations in the neural system, they reveal meaningful covariation between looking and discrimination that arises from how looking is coupled to cognition. In particular, stochastic fluctuations in the fixation, perceptual, and working memory systems cause variations in what is learned over the first few trials; these differences in learning then cascade over time to produce meaningful variations in performance at test. Note, however, that not all individual differences in looking are emergent during the course of a testing session. Some individual differences are stable across the first year (e.g., Colombo et al., 1987; Rose et al., 2001) and are, therefore, likely to reflect the developmental state of each individual infant.

An important future direction will be to further investigate the multiple influences on looking and learning at the level of the individual. Stochastic fluctuations in looking are one source of individual differences. Infants' long-term history with the stimuli can also influence learning (Kovack-Lesh et al., 2008; Quinn, Yahr, Kuhn, Slater, & Pascalis, 2002). Other studies show that individual differences in neonatal experience, as in preterm infant populations, can influence looking and learning (Rose et al., 2001). Finally, motor dynamics of the body can influence looking (Robertson et al., 2001). Grappling with this complex picture is critical to understanding developmental change at the individual level. I contend that computational modeling can play an important role in tackling this challenge.

In Chapter 6, I asked whether looking and discrimination follow the same developmental trajectory in at-risk infants as in typically developing infants. This is an important question because at-risk infants exhibit delayed performance relative to typically developing infants on looking measures and recognition performance. Such differences are assumed to reflect impaired processing speed. Results from Chapter 6 were consistent with this: there were robust changes in speed of processing between the

4- and 10-month-old data sets– shift rate increased, look duration decreased, and peak looks decreased with age. Moreover, regression analyses revealed that these changes in speed of processing captured a significant proportion of variance in discrimination performance. Thus, as in the typically developing sample, speed of processing and discrimination were linked at the individual level.

Nevertheless, there were differences in discrimination across populations – young at-risk infants, as a group, discriminated the familiar and novel items on the three step test, while older at-risk infants did not. This raises the possibility that discrimination in at-risk infants may be U-shaped, that is, at-risk infants older than the group tested in Experiment 3 might show robust discrimination on the three step test. This also raises the question of why young at-risk infants discriminate the three step test, but young typically developing infants do not. An intriguing possibility is that the slower shifting, longer look durations, and longer peak looks of young at-risk infants facilitates memory formation. Reversely, the faster shifting, shorter look durations, and shorter peak looks of older at-risk infants hinders memory formation.

I contend that such questions are open to direct investigation using methods comparable to Jankowski et al. (2001). These researchers experimentally manipulated infants' looking dynamics and altered recognition performance. Interestingly, Jankowski et al. found that increasing shifting and shortening look durations improved discrimination. This is the opposite pattern from what I observed with the preterm sample. The reason for this difference might be that different patterns of looking may facilitate learning about and discriminating among simple, two-dimensional objects such as those used in this thesis and the high-dimensional geometrical patterns used by

Jankowski et al. More specifically, fast shifting may foster sampling of multiple dimensions across looks, increasing the likelihood that a remembered dimension is recognized at test. Slow shifting, by contrast, may reduce the number of dimensions sampled, leaving multiple dimensions relatively novel across familiar and novel stimuli at test.

A long-term goal of the work presented in this thesis is to develop tools for assessing cognition in atypically developing populations and to develop interventions that foster positive developmental outcomes. Assessment requires a procedure sensitive to population differences in looking and cognition. The VPC may be a candidate procedure. Indeed, Chapter 6 showed that the variant of the VPC used here produces comparable cross-population differences to the variant of the VPC used by Rose et al. (2001). Together, this suggests that the VPC may be more sensitive to population differences than Rose et al's (2002) processing speed task or Rose et al's (2001b) serial recognition task that did not yield population differences. Using looking as a behavioral assessment tool, however, requires a much richer understanding of the link between looking and cognitive dynamics across populations than has, at present, been achieved. Experimental manipulations of infants' looking, like those described above, take an important step in this direction.

Intervention, however, requires a somewhat different understanding. Intervention requires an understanding of embodied, dynamic exploratory systems as captured by the DNF model. One implication of such a model is that it can autonomously look, as infants do, at a world that includes dynamic, stimulating events. This provides a critical link to studying how social partners influence looking and cognitive dynamics in infancy. For example, parents can positively impact atypical development by modulating where infants look. Parents of preterm infants who maintain their infants' gaze on the object they are currently exploring, rather than redirecting to other non-fixated objects, have infants who look at more objects and initiate joint attention more (Landry & Chapieski, 1988). Moreover, intervention studies that train parents to maintain their 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 exploration of how such manipulations impact learning in the moment and accumulate to create developmental change in cognition.

Consider a hypothetical example. If the DNF model were exploring a task space with multiple objects, the duration spent looking at a given object could be influenced by whether or not the object was manipulated by a social partner. This would prolong looking and, in turn, facilitate memory formation. Memory is then carried forward in time, facilitating memory formation for similar items upon subsequent encounters. Those objects are recognized more quickly, biasing the system to explore and learn about new items.

This thesis made important strides toward the overarching goal of attaining a richer understanding of the link between looking and cognitive dynamics. However, there are some limitations that must be resolved to fully achieve this goal. My method for examining this link was to use a neural network model that captures basic perceptual and memory process that are generally agreed to underlie infant looking behavior (Cohen, 1973; French et al., 2004; Hunter & Ames, 1988; Oakes et al., 2008). I captured developmental change in looking by manipulating parameters that govern these basic processes in the DNF model. The model was able to reproduce infants' behavior at qualitative and quantitative levels.

One limitation, however, is that developmental change was captured by hand – that is, as the modeler I manipulated parameters that produced expected and necessary changes in cognitive dynamics to capture behavioral changes. The system itself did not create its own development. In principle, real-time neural activity could be strengthened via an experience-dependent, autonomous process. This would enable active neural populations to interact more strongly upon future encounters with the stimulus. Such strengthening of active connections is similar to the Hebbian process implemented here. It is possible that such processes play an important role when carried forward across the longer timescales of development. Future work will be needed to probe candidate mechanisms of developmental change to see whether a neural system like the one used here can create its own developmental changes over time.

A second limitation in the present work is that I captured developmental change in behavior by exclusively manipulating cognitive parameters. This is consistent with the widely accepted view that developmental change in looking arises from changes in cognition. Nevertheless, this view neglects dramatic changes in motor control during the first months of the first year that do impact looking dynamics (Robertson, Bacher, & Huntington, 2001; Robertson & Johnson, 2009). In an exploratory system, such as the DNF model, a slightly slowed or, reversely, speeded release of fixation can make a substantial contribution to the time course of memory formation. One avenue for future research will be to explore relations between motor and memory dynamics.

In closing, let me revisit the contribution of the theoretical model developed in this thesis to our understanding of looking and cognitive dynamics, and the contribution of theoretical models to developmental science more generally. It is not always clear whether the field of developmental science values computational modeling (for a discussion, see Simmering, Triesch, Deak, & Spencer, 2010). Yet, formal neural network models have been used in developmental science for decades. In this thesis, I presented 19 simulation sets and a total of 11,200 simulations. The question is: did this simulation work enhance this thesis beyond what it may have been without it? I believe that it did. First, the ability of the DNF model to capture developmental change in looking, recognition, and discrimination expands the range of possible mechanisms that may underlie these cognitive and behavioral changes (for a similar discussion, see Thomas, 2000). Second, the DNF model enabled me to test whether the same developmental mechanism – the SPH – that captures changes in children's spatial memory abilities can also capture developmental change in infant looking and memory. This is a critical test of the generality of the SPH. The SPH appears to be quite general and captures constraints that appear necessary to explain a rich pattern of looking and learning over the first year. This also highlights another contribution of the DNF model to this thesis: the dynamic field framework is a useful tool for testing theoretical assumptions.

Next, a well-tuned model makes contributions beyond the specific data sets under consideration. Consider the potential role of test order discussed in Chapter 5. In Experiment 1, I found that looking indices of processing speed were predictive of discrimination on the three step test. By contrast, in Experiment 2, I found that looking indices of processing speed were predictive of discrimination on the one step test. One potential source of this cross-experiment difference was that one age was tested with counterbalanced test orders in Experiment 1, while three ages with a single test order were probed in Experiment 2. Testing this possibility experimentally would be costly and laborious. Instead, I used the DNF model to shed light on this issue by running a simulation experiment. Such simulation experiments could help answer open questions that arise from experimental data that are simply impractical to answer.

The results of such simulation experiments, however, are only as good as the parameter settings of the model. This reveals two challenges for computational modeling in developmental science. The first challenge is that parameters sometimes need to be modified to capture a new data set with an existing model (French et al., 2004; Mareschal, French, & Quinn, 2000). This leads to a common criticism of computational modeling, that any pattern of data can be fit with enough parameter hunting. There is certainly *some* merit to this criticism. For instance, the DNF model used here could have captured the developmental results from Chapter 5 in much more detail if I freely manipulated parameters. So, why did I not? The parameters I changed were motivated by a theoretical constraint – the SPH. The modeler has a responsibility to use such constraints where available. But when a model succeeds in a constrained setting, this should help overcome concerns about parametric change across contexts. In such settings, it is generally not the case that *any* pattern could be modeled.

The second problem is determining the usefulness of a model and a specific parameter set, as well as the usefulness of proposed developmental mechanisms. One method for addressing this problem is to capture a wide range of data across tasks and to generalize developmental mechanisms across domains. The work in this thesis makes an important contribution in both senses. I successfully generalized the DNF model from single presentation habituation to the visual paired comparison task. Moreover, I generalized the SPH from the domain of spatial cognition to the domain of visual recognition in infancy. Both forms of generalization lend credence to the usefulness of the DNF model and the SPH. Another way to probe usefulness, of course, is to generate novel predictions and test them empirically. Chapter 4 demonstrated that the DNF model was up to this challenge as well: I used the model to test a radical prediction that infants, under special circumstances, would show a familiarity and novelty bias late in learning. In summary, then, I contend that the rich theory-experiment link in this thesis has provided a deeper understanding of how looking and cognitive dynamics are linked in infancy. It is in this link – not a particular model or parameter setting - that I believe will foster new scientific breakthroughs in the years to come as researchers fully embrace the autonomous, exploratory nature of looking and learning in infancy.

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