CHAPTER TWO

Applications of Dynamic Systems Theory to Cognition and Development: New Frontiers

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Abstract

A central goal in developmental science is to explain the emergence of new behavioral forms. Researchers consider potential sources of behavioral change depending partly on their theoretical perspective. This chapter reviews one perspective, dynamic systems theory, which emphasizes the interactions among multiple components to drive behavior and developmental change. To illustrate the central concepts of dynamic systems theory, we describe empirical and computational studies from a range of domains, including motor development, the Piagetian A-not-B task, infant visual recognition, visual working memory capacity, and language learning. We conclude by advocating for a broader application of dynamic systems approaches to understanding cognitive and behavioral development, laying out the remaining barriers we see and suggested ways to overcome them.

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1. DYNAMIC SYSTEMS THEORY

Dynamic Systems Theory (DST) is a set of concepts that describe behavior as the emergent product of a self-organizing, multicomponent system evolving over time. This chapter reviews the progress DST has made in the domain of cognitive and behavioral development, the promise we see in further applications of this perspective, and our vision of how the field may meet challenges that are yet unmet. The application of DST to human behavior that we describe here is rooted in Thelen and Smith's (1994) book, *A dynamic systems approach to the development of cognition and action*, in which they proposed a bold rethinking of human cognition, behavior, and development. They took inspiration from at least two sources. One source was the complex models of other physical systems that did not reduce them to their elementary parts but embraced their complexity as an interactive whole. Such physical models span domains, including chemical phenomena such as crystal growth, oscillating movements of a spring or pendulum, flow patterns in water and air, cloud formation, and more. Thelen and Smith (1994; see also Fogel & Thelen, 1987) recognized a remarkable parallel between complex physical systems and human behavioral development, and sought to formally apply the same concepts across these domains.

Another source of inspiration was the theoretical climate in developmental psychology in the 1980s and 1990s (for an example see Haith, 1998). In the domain of cognitive development in particular, historical views of infant cognition as being constructed from sensorimotor origins were being replaced with the view of the infant as a precocious learner with, perhaps, inborn competencies (e.g., Spelke, 1985). For example, measures of infant looking behavior were beginning to be interpreted as reflecting conceptually based cognition about objects and events rather than the perceptual and memory processes more characteristic of interpretations espoused throughout the 1960s and 1970s (see Perone & Ambrose, 2015; Perone & Spencer, 2013b). These views were often built upon faulty empirical foundations (for example, see Baillargeon, 1987; and critiques by Cashon & Cohen, 2000; Rivera, Wakeley, & Langer, 1999; Schöner & Thelen, 2006), leading Thelen and Smith (1994) to advocate for bringing sophisticated theory and methodological rigor into research on child development.

The goal of this chapter is to illustrate the application of DST concepts to cognitive and behavioral development. This chapter is divided into four sections. In the first section, we provide a review of several foundational DST concepts. In the second section, we describe a formal instantiation of DST concepts into a computational framework called the Dynamic Field Theory that we and our colleagues have used as a tool to understand cognition, behavior, and development. We will illustrate how formal models that simulate behavioral and cognitive dynamics have yielded new insights and advanced the application of DST to human behavior. Although our own "home territory" is the application of computational tools, there are many excellent noncomputational applications of DST as well, which we describe in the third section. In the last section, we sketch a road map for advancing DST in the domains of cognition and development, broadly defined.

1.1 Foundational Concepts

DST has been applied to human cognition and development both as a conceptual framework and as a literal description of a dynamic system. We contend that both approaches are valuable and enrich our understanding. Our review of DST concepts is not an exhaustive list but instead focuses on those most foundational to the study of cognitive development. DST applications within psychological science have not been unitary. At the 2009 biennial meeting of the Society for Research in Child Development, a panel discussion of dynamic systems as a metatheory presented four "camps" of DST (see Witherington, 2007 for similar discussion). These camps all adopt the foundational concepts that we review here, but differ in the domains of application, the relative emphasis on different features of DST, and the philosophical perspective on what can (or cannot) be understood about the mental structures that underlie behavior (for further discussion see, e.g., Fogel, 2011; Hollenstein, 2011; Lewis, 2011; Spencer, Perone, & Buss, 2011; van Geert, 2011; van Geert & Steenbeek, 2005; Witherington & Margett, 2011). We come from the "Bloomington camp" associated with Thelen and Smith, and therefore primarily present examples from this "family" of researchers. Although we acknowledge the differences between camps as meaningful and consequential for research programs, we see great value in integrating conceptual and methodological variants across camps to achieve our ultimate goal: to understand how development happens. In the context of explaining cognition and development, we consider three concepts to be central: multicausality, self-organization, and the nesting of timescales.

The foundational DST concept of *multicausality* refers to the convergence of multiple forces to create behavior. The contributions to behavior in the moment include a person's body, age, mental state, emotional state, social context, personal history, and more. Furthermore, in dynamic systems no single factor is more important than any other—only through the combination of all factors together does causation occur, so it is illogical to consider any given factor in isolation. Proponents of DST emphasize an appreciation for mutual, bidirectional dependencies between brain and behavior, rather than considering behavior to be driven primarily by a single component (i.e., the brain). This aspect of DST has sometimes been criticized as making research intractable, as it is impossible to measure or control every potential contributing factor. As we illustrate in subsequent sections, however, we contend that multicausality can inform research design, implementation, and interpretation through the questions we ask with our studies, the way in which we gather information, and how we extrapolate from our results.

A second foundational concept is *self-organization*. The behavior of a system is an emergent product of multiple components interacting through time, interactions that are context dependent. Self-organization is related to a collection of additional DST concepts. Systems organize into what are called *attractor states*, which are ways in which the components of a system reliably interact (e.g., crawling, walking, and running are different attractor states for locomotion). Systems are *historical*, which means that their organization in an attractor state in the moment biases them to revisit those attractor states at a future point in time (Spencer & Perone, 2008). These states become increasingly *stable* through experience, which means that they are resistant to perturbations from internal and external forces. Systems are *open* to the environment, which means that external forces can shift the components of a system into a new way of interacting, which can often be *nonlinear*.

The last foundational concept is the *nesting of timescales*. The timescale of neural firing is nested within the timescale of cognition, which is nested within the timescale of behavior over learning and development. The strong claim of DST is that these timescales create each other. Consider a prevalent example from developmental science. Typically, we study children's behavior in the lab at one point in time and then at another point in time. This provides good insight into developmental differences. Developmental change, however, happens in between lab visits via massive quantities of real-time processes that occur across multiple levels. How do the neural processes, brain-wide dynamics, and movement that are involved in the behavioral decisions children make on a daily basis create developmental change? This is a central challenge for DST. This is illustrated in a case study described in a subsequent section that uses a computational model of infant looking behavior.

The three central concepts we described here—multicausality, self-organization, and nesting of timescales—are each interconnected in the empirical phenomena that illustrate them. Thelen's early application of DST concepts to development was in the motor domain, considering changes in infants' stepping, reaching, and posture (see Spencer, Clearfield, et al., 2006 for review). But this subdomain of developmental psychology had become increasingly distant from the study of infant cognition, as researchers began to posit more complex and mature "concepts" that supported infant behavior. A critical challenge for DST was to move from the mechanics of motor development—where analogies to physical systems were easier to understand and appreciate—into the domain of human thought, which is often treated as qualitatively different from motor behavior. A first step in this direction was taken as Thelen, Smith, and colleagues applied DST concepts to Piaget's A-not-B task, purported to index the concept of object permanence in infants. This work illustrated the parallel between motor and cognitive development and, critically, their inseparability. Thus, we turn to a discussion of the Piagetian A-not-B error as an influential and historically important application of DST.

1.2 The Piagetian A-Not-B Error

The classic A-not-B paradigm can be used to illustrate the central concepts of DST explanations of cognition and development. In this task, an infant is seated in front of a box with two lids covering wells to hide a toy; an experimenter hides a toy in one well (the A location) and the infant retrieves it. Following a few repetitions at the A location, the experimenter hides the toy in the other well (the B location). When allowed to reach for the toy after a short delay, infants younger than 10–12 months of age will erroneously search at A, whereas older infants will search correctly at B. Two types of explanations dominated the literature prior to the DST conceptualization. First was Piaget's interpretation that this "A-not-B error" indicated a lack of object permanence—a qualitative developmental change, the acquisition of a new cognitive structure, explained older infants' success (Piaget, 1954). This perspective was challenged by evidence that infants' behavior could be modulated through changes in the task structure. Thus, a second class of explanations emerged in which young infants' errors were attributed to limitations in basic cognitive processes, such as attention, inhibition, and/or memory (e.g., Diamond, 1985; Marcovitch & Zelazo, 1999; Munakata, 1998). Critically, these theories posited that these processes were present in younger infants, but merely ineffective under the demands of the task: the change in behavior arose through quantitative improvements in existing processes rather than a new cognitive ability.

As a new view on the A-not-B error, Thelen and Smith (1994; see also Smith & Thelen, 2003; Smith, Thelen, Titzer, & McLin, 1999) presented a DST account in which multiple causal components came together in the context of the task (self-organized) to produce the characteristic error. In contrast to Piaget, they argued that there was no specific concept that supported successful performance in this task, but rather infants' actions in the task emerged from the confluence of components (Smith et al., 1999). To understand developmental change in behavior, then, required studying how reaching decisions were made in the specific task context. Thus, it was not only the case that individual components of the system were improving developmentally, but also how these components were brought to bear on the task at hand. In addition to attention, inhibition, and memory (processes highlighted independently in previous explanations; Diamond, 1985; Marcovitch & Zelazo, 1999; Munakata, 1998), Thelen, Smith, and colleagues showed how behavior was influenced by motor planning, posture, and features of the task space (see Smith & Thelen, 2003 for review). Most critically, no single process or component was central in their theory; rather, behavior depended on the convergence of all components together, and the manner in which they combine may vary according to task demands.

Smith et al. (1999) argued that we should focus on describing and explaining what we can measure—behavior—and not conflate that with the underlying knowledge we aim to understand. They demonstrated, for example, that the error occurs in the absence of objects: cueing infants to reach only by lifting the lid showed the same developmental transition from perseveration to correct reaching on B trials; without hidden objects, a concept of object permanence could not explain this change. An infant's reach on any given trial (whether the A or B side was cued) was influenced by the infant's history of reaches in the task and the direction of their visual attention in the moment. Thus, where an infant looked and reached before, and where they looked right before reaching, all contributed to their reaching behavior on a trial-by-trial basis.

Additional analyses of reaching trajectories showed how the history of reaches built up across trials, with a more stable reach in the moment leading to a stronger influence on future reaches (Diedrich, Thelen, Smith, & Corbetta, 2000). Further studies connected this behavior in the moment of the task to developmental changes in task performance. Very young infants, with immature reaching abilities, do not perseverate in the A-not-B task; rather, stable reaching on A trials is necessary to form the memory traces that produce errors on B trials (Clearfield, Smith, Diedrich, & Thelen, 2006). These studies illustrated that the history of reaching in the task is not independent of those specific reaches: unstable reaches leave weak traces that exert little influence on future reaches. Longer-term experience with reaching increases the stability of reaching, which first allows for the emergence of the error (Clearfield et al., 2006) and later allows infants to overcome the error by maintaining a stable plan to reach to the B location (described further later; Thelen, Schöner, Scheier, & Smith, 2001). These findings, along with many others (some of which are described later), provide a compelling demonstration of how the self-organization of multiple components produces behavior in the moment, connections across timescales, and the many sources of change over development.

Although this line of work uncovered a vast range of influences on infants' and older children's search abilities, the illustration of dynamic systems concepts through the A-not-B error has been a double-edged sword: it allows for clear description and manipulation of the many factors that will influence infants' behavior, but it also led to the erroneous impression that systems perspectives are best suited to explanation of fairly simple sensorimotor tasks and development during infancy. An inherent challenge in the application of DST to cognition and brain processes is that one cannot directly observe and measure them in the way sensorimotor behaviors can be. Tackling this challenge requires an application that connects cognitive and brain processes to behavior as a dynamic system. This was a driving force behind the application of computational models to explain cognitive and behavioral processes in development, which we turn to next.

2. THE DYNAMIC FIELD THEORY AND DYNAMIC NEURAL FIELDS

Our own research programs incorporate a style of computational modeling that formally implements cognitive, neural, and behavioral processes as dynamic systems. These types of models are called dynamic neural fields (DNFs) and embody a set of concepts from the Dynamic Field Theory. The Dynamic Field Theory extends DST to neural population dynamics to bridge brain and behavioral dynamics (Spencer & Schöner, 2003). The overarching goals of this approach have been detailed in an edited volume entitled *Dynamic thinking: A primer on dynamic field theory* (Schöner, Spencer, & The DFT Research Group, 2015). The volume includes a collection of chapters that each describe a particular computational model architecture and its application(s), with exercises to explore the model using interactive simulators provided with the book. Here we provide examples from a subset of these applications within visuospatial cognitive development to illustrate central characteristics of the approach, to highlight the models as formally implementing the concepts of DST. A key benefit of this computational approach is the formalization of not only the processes that support the central cognitive processes such as encoding, maintenance, and comparison of items in memory but also the specific types of behavior measured in each task. This allows for a systematic analysis of what types of memory processes might be necessary and sufficient for specific behavioral patterns to emerge in a task.

We provide a brief introduction to DNFs and then describe three case studies that illustrate the use of DNFs to implement key DST concepts. Because these concepts are necessarily interrelated, each case study can be used to illustrate multiple concepts, but we chose to emphasize specific concepts that are particularly salient in each case.

2.1 Introduction to DNF Models

DNFs belong to a larger class of bistable attractor networks (Amari, 1977; Wilson & Cowan, 1972). DNFs simulate neural populations tuned to represent a continuous dimension, such as space or color. DNFs represent these populations through functional topography such that neurons representing similar feature values (e.g., shades of blue) are next to one another within the field. The unit of cognition in DNFs is the "peak," which is a real-time neuronal representation of a stimulus that supports behavioral decisions. For example, a working memory representation of a blue stimulus emerges from the excitation of neurons selectively tuned to its hue. This, in turn, leads to the excitation of neighboring, similarly tuned neurons (i.e., representing other shades of blue) and inhibition of more distant, dissimilarly tuned neurons (i.e., representing red, orange, and yellow). The result is a localized peak of activation that is a dynamically stable attractor state. Multiple fields (also called layers) can be coupled together in a variety of ways to create more complex model architectures to simulate different neurocognitive functions (e.g., movement planning, attention, memory), as described in the case studies in the following section.

DNFs are dynamic systems, and thus, a key feature of these models is that they are influenced by their own history. The cases we will consider include a simple mechanism of learning, the laying down of memory traces by active nodes that facilitate activation of those same nodes in the future. Peaks leave memory traces that strengthen activity among active neurons in a Hebbian fashion (Perone & Ambrose, 2015; Perone & Spencer, 2013a). This primes those neurons to respond more strongly to a similar stimulus at a future point in time. For example, a peak representing a blue item leaves a memory trace associated with the color blue that, in turn, facilitates the formation of a peak associated with the color blue if it is presented again. This simple memory trace mechanism enables real-time experience to be carried forward in time to influence cognitive and behavioral dynamics across a longer timescale. This feature can shift DNFs into qualitatively different modes of operating and have a big impact on behavior by, for instance, enabling DNFs to remember more items simultaneously (see Perone, Simmering, & Spencer, 2011; Simmering, 2016; Simmering, Miller, & Bohache, 2015).

A unique feature of DNF models is that they can be situated in the same task context as participants to simulate self-organization. For example, a DNF model can be presented with objects that vary along color and shape dimensions, that are presented in different locations, and that are associated with different labels. Memory along any of these dimensions (features, locations, labels) can then be probed through different types of behavioral responses (e.g., selecting one from a set of choices, explicitly judging "same" or "different," fixating, estimating a feature or dimension) depending on the task demands. This feature of DNFs has yielded numerous novel insights about the connection between cognition and behavior across tasks (for specific examples of different response types in the same system, see Samuelson, Schutte, & Horst, 2009; Simmering, 2016; Spencer, Simmering, & Schutte, 2006).

2.2 DNFs Are Dynamic Systems: Three Applications

DNFs have been applied to a diverse range of phenomena. We selected three examples from our own repertoire that illustrate how DNFs embody DST concepts, foster understanding of the link between cognitive and behavioral dynamics in a theoretically rigorous fashion, and provide a tractable road map to guide empirical research. Within each of these examples, the same underlying concepts can be found, but the relative emphasis on each concept varies. We highlight one concept within each of the sections, but do not intend to imply that the concepts can be separated entirely.

2.2.1 Multicausality in the Piagetian A-Not-B Error

As a first example, we consider model simulations of performance in the classic A-not-B task and variants that have followed to test specific predictions. As described earlier, the A-not-B task was proposed by Piaget (1954) to assess object permanence, whereas other researchers argued that task failures reflected immature cognitive processes like attention, memory, and/or inhibition (e.g., Diamond, 1985; Marcovitch & Zelazo, 1999; Munakata, 1998). Thelen et al. (2001) proposed a model that focused on movement planning (cf. Erlhagen & Schöner, 2002). Movement direction was instantiated as a continuous DNF, and activation on a given trial was influenced by the discrete hiding locations of the A-not-B task, the specific hiding event (toy at A or B), and the history of reaches on prior trials. Integration of these internal and external contributions showed concretely how a plan to reach evolved over the timescale of each trial in the task. The output on each trial was the location (A or B) that corresponded to the movement direction with maximal activation. Over time, within and across trials, activation in the motor planning field left a memory trace, which influenced subsequent activation (as described earlier). These characteristics together allowed the model to perform the A-not-B task: task input at the beginning of each trial represented the hiding locations, a specific input signaled the hiding event, then activation in the field propagated throughout the delay, and with the most active location at the end of the trial read out as the reach direction. Over repeated trials as experience accumulated, the memory trace from activation within the field served as another source of input, reflecting the history of planned and executed reaches in the task.

With a DNF model constructed to incorporate the important details of the task that influences performance, the final step was to consider potential sources of developmental change. In contrast to invoking a new cognitive construct to account for the transition from failure to success in the A-not-B task (such as object permanence; Piaget, 1954), Thelen et al. (2001) implemented a continuous change in the cooperativity of the movement planning field to simulate development. Specifically, they modified functional interactions among neighboring nodes by increasing the resting level of the field. With a higher resting level, the same magnitude of inputs to the model created stronger effects, with more robust formation and maintenance of peaks reflecting memory of the hidden object (see Simmering, Schutte, & Spencer, 2008 for an alternative instantiation of this concept in a more complex architecture). Thelen et al. showed how this DNF model could account for perseverative reaching early in development and correct reaching later in development, as well as the fact that perseveration only occurs with a delay between hiding and search (cf. Gratch, Appel, Evans, LeCompte, & Wright, 1974). They also simulated the effects of changing target distinctiveness, in which infants are less likely to perseverate when the lid for the B location is highly distinct from the A location and background (Diedrich, Highlands, Thelen, & Smith, 2001). The model architecture and simulations illustrate the multiple influences on infants' performance in A-not-B tasks, combining the structure of the task (lids, objects, delay), the internal dynamics of movement planning, and the history of reaches in the task, to predict reaching on a given trial.

Beyond the simulations presented by Thelen et al. (2001), this formalization (and subsequent adaptations of the model architecture) led to a number of specific predictions and new explanations of infants' behavior in the A-not-B task. For example, Clearfield, Dineva, Smith, Diedrich, and Thelen (2009) showed the interaction between the salience of the reaching locations and the delay implemented in the task. With the lowest and highest salience of the lid at B, perseveration was uniformly high or low, respectively, regardless of the delay between hiding and search. With a moderate level of salience, however, perseveration after no delay was low, but increased when a delay was added. Thus, the influence on reaching was not affected solely by salience or delay, but rather by the nonlinear combination of these factors.

A similar model was applied to results from another lab seeking to test the influence of social cues on A-not-B performance. Topál, Gergely, Miklósi, Erdőhegyi, and Csibra (2008) tested infants in three conditions of the A-not-B task with varying levels of social engagement by the experimenter. Perseveration decreased with reduced social engagement, which the authors interpreted as evidence that the social pragmatics of the task induced perseveration. In particular, they argued that infants misinterpret the social cues from the experimenter as indicating the object will continue to be found at the A location even after it is hidden at B. Spencer, Dineva, and Smith (2009) simulated these results in a DNF model, showing that the difference across conditions could be explained through the relative strength of encoding the hiding event: with high (typical) social engagement, the hiding event was encoded weakly (due to competition for attention), and the strength of encoding increased as social engagement decreased. Spencer et al. argued that the results from Topál et al. add to the broad range of conditions the DNF model could account for, and further illustrate the importance of considering how multiple factors contribute to performance in laboratory tasks.[a]

Beyond infancy and the A-not-B task, the general notion that spatial responses in a task are influenced by memory traces from past trials has been extended much later in development. Spencer and colleagues showed that toddlers and older children make A-not-B-type errors in a continuous space: searches for a toy hidden in a sandbox showed influence of past searches (Schutte, Spencer, & Schöner, 2003; Spencer, Smith, & Thelen, 2001) as well as memory for other locations even in the absence of past reaches (Spencer & Schutte, 2004). Spencer and colleagues also developed a similar task in which targets are presented on a large homogeneous table (rear-projection surface) and participants point or use a mouse to click on the remembered location. In this task, 3- to 11-year-old children and adults also show the influence of previous responses (Hund & Spencer, 2003; Lipinski, Simmering, Johnson, & Spencer, 2010; Schutte & Spencer, 2002; Spencer & Hund, 2002, 2003) as well as visual feedback (Lipinski, Spencer, & Samuelson, 2010). Note that, across these various studies of spatial cognition and development, some predictions and explanations have been derived from quantitative model simulations, whereas others have been motivated solely by the conceptual features of the theory (e.g., Simmering & Spencer, 2007). Thus, although formalization in a model can provide quantitative predictions, it is also possible to use the concepts embodied in such formalizations to generate qualitative predictions as well.

[a] Topál, Tóth, Gergely, and Csibra (2009) responded to Spencer, Dineva, et al.'s (2009) alternative explanation by testing a fourth condition, in which the social engagement from the experimenter was high on A trials and low on B trials. Infants in this study showed high perseveration, which Topál et al. argued contradicted the DNF model. However, they did not consider the fact that the sudden change in engagement between A and B trials likely drew the infants' attention more strongly to the experimenter (cf. the "still-face paradigm" by Tronick, Als, Adamson, Wise, & Brazelton, 1978), which would predict weaker encoding on B trials leading to high perseveration. This example highlights the importance of considering the full task context not only in the influence of the history of reaches but also in the history of the experience in the task more generally.

2.2.2 Self-Organization in Visual Working Memory Capacity

Our second example is a bridge between work with infants and later development, moving from the sensorimotor foundations that are apparent in reaching studies to higher-level cognition: working memory. Working memory has been identified as a vital cognitive skill that underlies many complex behaviors (Baddeley, 1986). In this section, we focus on studies of visual working memory (which is at least partially separable from verbal working memory in early childhood; Alloway, Gathercole, Willis, & Adams, 2004), as it can be studied over the life span (including infancy) and it predicts higher cognitive skills both longitudinally (e.g., Rose, Feldman, & Jankowski, 2012) and concurrently (e.g., Cowan, Fristoe, Elliott, Brunner, & Saults, 2006). We specifically consider capacity limits for nonspatial visual information (the "visual cache" described by Logie, 1995) and how they are estimated from lab tasks.

The concept of self-organization is most apparent when considering how performance differs across variations in task details. Simmering and Perone (2013) surveyed the literature on working memory development and found that estimates of capacity varied dramatically across studies, even when the general structure of the task and age group was the same. One way to address the variation due to task structure is through the use of DNF models, which allows researchers to situate the same cognitive system in different tasks and then to "look inside" to see how cognitive functioning compares between tasks. Simmering (2016) took this approach to understand an apparent contradiction in the literature on visual working memory capacity estimates. In particular, prior studies suggested that capacity increased from one item at 6 months to four items by 10 months (Ross-Sheehy, Oakes, & Luck, 2003), but was limited to only two or three items during the preschool years (Riggs, McTaggart, Simpson, & Freeman, 2006; Simmering, 2016). These inconsistent estimates were presumed to arise from the different behavioral tasks used across age groups (Cowan, 2007; Riggs et al., 2006), but no theoretical account had been proposed to explain precisely how and why estimates differed across tasks.

Simmering (2016) proposed that the same memory processes supported performance over tasks and development, and that understanding how the tasks relate could be achieved through formalizing the tasks into the same DNF model. The paradigm used to assess visual working memory capacity in young children and adults was the change-detection task (see Vogel, Woodman, & Luck, 2001 for task development), shown in Fig. 1A. On each trial in this task, a small number of simple items (i.e., colored squares, white

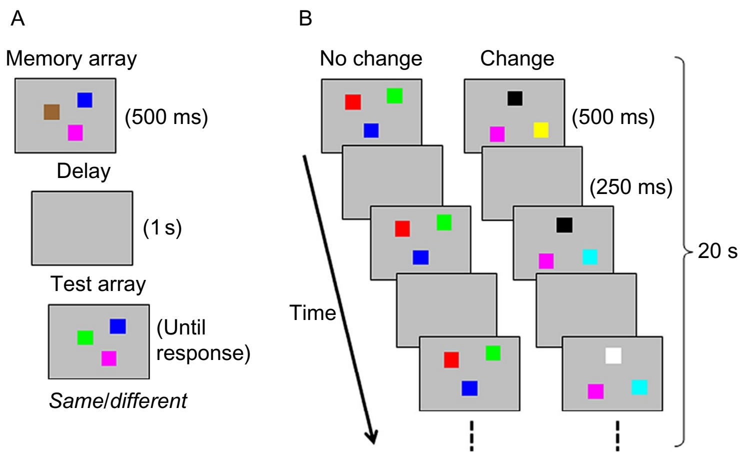

Fig. 1 Schematic illustrations of tasks used to assess visual working memory in (A) children and adults vs (B) infants; both present examples of set size three. *Adapted from Simmering, V. R., & Perone, S. (2013). Working memory capacity as a dynamic process.* Frontiers in Developmental Psychology, 3*, 567. http://doi.org/10.3389/fpsyg.2012.00567.*

shapes, oriented bars) are presented briefly in a memory array. After a short delay, a test array is presented and the participant is asked to judge whether the items in the test array are "same" or "different" compared to the items in the memory array. Across trials, the set size (number of items per memory array) may vary, and performance typically declines as set size increases. Capacity can be estimated from this task using a formula proposed by Pashler (1988), in which K is the estimated number of items held in memory, calculated from the proportion of hits (i.e., correct "different" responses) relative to the total number of items in the memory array (set size) with correction for "guessing" (i.e., incorrect "different" responses).

Ross-Sheehy et al. (2003) developed a task for infants motivated by the design of the change-detection task. Because infants cannot explicitly judge arrays as "same" or "different," Ross-Sheehy et al. capitalized on infants' tendency to prefer looking to novel displays (e.g., Fagan, 1970) in a preferential looking paradigm. For this change-preference task, shown in Fig. 1B, infants viewed two displays that each contained a small number of colored squares that blinked on (for 500 ms) and off (for 250 ms) repeatedly throughout the duration of a 20-s trial. On the no-change display, the colors remained the same across presentations; on the change display, one randomly selected color changed to a new color following each blank delay. The amount of time infants spent looking to each display was tabulated across the trial, and the proportion of time that was directed toward the change display was used to calculate a change-preference score. Mean change-preference scores that were reliably above chance (0.50) were interpreted as evidence of memory for the items in the array: if the infants could remember the colors, they would be able to detect that one color was changing in the change display and it would appear more novel than the no-change display. Ross-Sheehy et al. used this task to estimate infants' capacity by comparing performance across multiple set sizes, varying the number of items in each display, and assuming capacity for the highest set size at which the age group showed a robust change preference. Estimates of capacity during infancy suggested a rapid increase, from remembering only a single item at 6 months to remembering four items at 10 months (Ross-Sheehy et al., 2003); follow-up studies indicated that infants could remember at least three items (no higher set sizes were tested) by 7.5 months (Oakes, Messenger, Ross-Sheehy, & Luck, 2009; Oakes, Ross-Sheehy, & Luck, 2006).

The estimates derived from the infant change-preference task were seemingly inconsistent with estimates derived from early childhood using the change-detection task, which indicate capacity of less than two items between ages 3 years (Simmering, 2012) and 5 years (Riggs et al., 2006). As potential explanations for this inconsistency, Riggs et al. (2006) hypothesized that the change-preference task might rely on a more passive type of memory than the change-detection task. Cowan (2007) proposed that estimates may differ across tasks due to different attentional demands. Simmering (2016), by contrast, examined how the same processes of formation, maintenance, and use of memory representations self-organized to produce different behaviors across tasks. Building from the type of model architecture developed to explain spatial working memory development (Spencer, Simmering, Schutte, & Schöner, 2007), Simmering and colleagues used a three-layer DNF architecture to account for performance across these two visual working memory tasks (Johnson, Simmering, & Buss, 2014; Perone et al., 2011; Simmering, 2016).

This architecture, shown in Fig. 2, includes two excitatory layers coupled to a shared inhibitory layer (see Johnson & Simmering, 2015 for review). The excitatory layers correspond to the perceptual processing vs working memory representation of information relevant to the task through different strength of connections. Weaker excitation and inhibition in the perceptual layer produces input-driven representations, that is, activation that remains above threshold only in the presence of input; this reflects

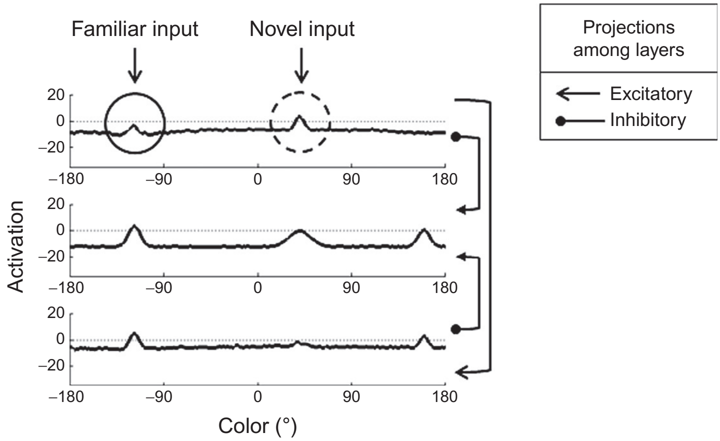

Fig. 2 Architecture of the three-layer dynamic neural field model used by Simmering and colleagues. This simulation shows two items held in the working memory field (WM; *bottom*) with two inputs projected into the perceptual field (PF; *top*), labeled as familiar vs novel. As described in the text, perceptual processing of the familiar item is suppressed due to shared inhibition (Inhib; *middle*). *Dashed horizontal lines* in each layer indicate the activation threshold for interactions among nodes.

perceptual processing of incoming visual information. Stronger excitation and inhibition in the working memory layer allows self-sustaining representations, with peaks maintaining above-threshold activation after input has been removed. Activation within and between layers interacts continuously throughout the task, with excitation projecting from the perceptual layer to the inhibitory and working memory layers, as well as from the working memory layer to the inhibitory layer, with inhibition projecting back into both excitatory layers (see Johnson & Simmering, 2015 for further details).

Fig. 2 shows a simulation of this architecture to illustrate the basic mechanisms of recognizing familiar feature values vs detecting novelty. In this simulation, color is the feature dimension represented along the horizontal axis; peaks in the bottom field represent two different color values that have been encoded into working memory. In the context of the change-detection task, this would be the case if two items had been presented in the memory array and were remembered throughout the delay. The middle inhibitory layer in this figure shows how coupling among layers can provide an emergent comparison process: when a peak is present within an excitatory field, activation projects to similarly tuned nodes within the inhibitory layer, which produces an inhibitory bump (note that the difference between "peak" and "bump" reflects the presence vs absence, respectively, of local excitatory interactions within the field). The inhibitory bumps project inhibition to the similarly tuned nodes in both excitatory layers, which slightly suppresses activation at these locations. When two inputs are presented in this simulation, as in the test array of a change-detection trial, one is a familiar value (i.e., a color held in working memory) and the other is novel. The peak in working memory that corresponds to the familiar item has an associated inhibitory bump, which leads to suppressed processing of this item in the perceptual field (see circle in Fig. 2). The input from the novel item, by contrast, projects into the perceptual field at a point where activation is closer to threshold (0, marked with a dashed line), which allows a peak to build. This above-threshold activation in the perceptual field serves as a signal of novelty, which can then be used to support task-relevant behavior.

In the change-detection task, the required "same" or "different" response has been implemented as a simple decision system that is coupled to the excitatory layers, such that activation in the perceptual layer projects to the "different" node and activation in the working memory layer projects to the "same" node (see Johnson et al., 2014 for further details). The decision nodes include self-excitation and mutual inhibition such that only one can achieve above-threshold activation, yielding a single response on each trial. For the change-preference task, a rudimentary fixation system can be linked to the perceptual layer (see Perone et al., 2011 for further details). This system includes nodes representing fixation of the left vs right display in a paired comparison task, as well as nodes representing central fixation and fixating away from the displays. The fixation system is reciprocally coupled to the perceptual layer, allowing it to serve as a perceptual "gate," such that input associated with a display only projects into the three-layer architecture when the corresponding fixation node activation is above threshold. When activation in the perceptual layer is above threshold, this activation projects back to the fixation system to support continued fixation. When combined with the mechanism for detecting novelty shown in Fig. 2, this leads the model to "prefer" looking at novel stimuli, similar to infants (see also Perone & Spencer, 2014).

Implementing both change-detection and change-preference tasks into the same model architecture allowed Simmering (2016) to analyze the causes and consequences of memory formation in these different task contexts. Model simulations revealed two important characteristics of the change-preference and change-detection tasks to help explain the apparent discrepancy in estimates across tasks. First, the different behaviors required by each task led to different relations between the underlying memory representations and the behavioral estimates. In particular, simulations of change-detection performance across multiple age groups and data sets have shown that capacity estimates using Pashler's (1988) K underestimate the number of items that must be held in memory to generate that level of behavioral performance. Three-year-old children's mean K_{max} estimates (i.e., maximum K across set sizes for each child; Simmering, 2012) were 1.90 items. Analysis of the number of peaks held in the working memory field on simulations that produced a comparable level of performance (K_{max} estimate of 1.99 across 20 simulations) showed an average of 3.23 peaks per trial. Across two studies, adults' mean K_{max} estimates were 4.58 (Johnson et al., 2014) and 4.62 (Simmering, 2016), and simulations fitting that performance revealed (respectively) averages of 5.79 peaks in set size six and 4.99 peaks in set size five. Thus, simulations of behavior suggest that K may underestimate the number of items held in memory (Johnson et al., 2014; Simmering, 2016). This is because the processes that generate behavior are not free of errors: there may be cases in which the items were held correctly in memory, but did not lead to accurate responses (see Johnson et al., 2014 for example).

In contrast to the change-detection simulations, behavior in the change-preference task appears to overestimate the number of items held in working memory. In particular, the same model architecture used to generate simulations of children's change-detection performance was also tested in the change-preference task (Simmering, 2016). Behavioral estimates indicated memory for at least six items in 3- to 5-year-old children and adults, reflected in robust preferences for the change display in set size six (the highest set size tested). Analysis of the contents of the working memory field, however, showed that the significant preferences in set size six could be supported by holding fewer items in memory (see Perone et al., 2011 for analogous results simulating infants' performance). In particular, Simmering calculated the mean number of peaks held in working memory in the final delay period of each change-preference trial (i.e., after 26 presentations of each display, with autonomous looking between displays). In set size six, where all age groups showed significant change preferences, the mean number of peaks ranged from 4.38 to 5.58 across parameter sets tuned to children's vs adults' performance. Thus, remembering a portion of the items presented was sufficient to support a preference for the change display, and the capacity assumed from this preference overestimated the contents of memory.

These simulations of change-preference and change-detection tasks demonstrated that capacity is not independent of the task, but rather emerges through self-organization of the memory system in the particular task context. Specifically, the structure of the task allowed the exact same memory system—computationally specified in a neural network model—to hold more items in memory in a more supportive context (i.e., the change-preference vs change-detection tasks; Simmering, 2016). This formalization provided an alternative to the explanations generated in the literature, in which the looking task was considered to possibly measure a more passive type of memory (Riggs et al., 2006), relative rather than absolute capacity (Ross-Sheehy et al., 2003), or rely on long-term memory or habituation rather than short-term memory (Oakes, Baumgartner, Barrett, Messenger, & Luck, 2013). Rather, capacity limits in visual working memory arise dynamically in the context or particular task structures, and estimates of capacity depend on the type of behavior required (see also Simmering & Perone, 2013). The dynamic systems explanation of capacity limits emerging through the constraints of the specific task and the developing cognitive system can provide a more comprehensive and parsimonious explanation of developmental change than prior theories.

2.2.3 Connecting Real and Developmental Timescales in Infant Looking

A central claim of DST is that there is nothing but real-time process: all further changes along longer timescales (i.e., learning and development) are created from the real-time scale. There is no governing agent in development, no road map telling development where to go, only real-time process and the history it creates (Smith & Thelen, 2003). This claim is bold, and a concrete theoretical understanding of how the real and developmental timescales are connected has remained elusive. To appreciate why this is so, consider just one common context in which most infants are situated on a daily basis—sitting among a cluttered array of toys. For simplicity, let us just consider a very short period of time, 1 min or less. In that snippet of time, an infant may look at a toy, switch gaze to mom, then to the dog, and then to a new toy. Next, the television may capture the infant's attention and gaze before switching gaze to yet another new toy, then to a sibling, and then back to the toy. How does this chaotic world create any sort of systematic developmental change?

Perone and Spencer (2013a) sought to answer this question in a series of simulations in the same three-layer model described in the preceding section. At issue is the robust observation that infants exhibit highly predictable changes in looking behavior in visual memory tasks over the course of the first year. For example, with age, infants' looking to a visual stimulus habituates more quickly (Colombo & Mitchell, 1990), they exhibit faster gaze switching, shorter look durations, and stronger visual recognition (Rose, Feldman, & Jankowski, 2001), discrimination becomes more precise (Brannon, Suanda, & Libertus, 2007; Perone & Spencer, 2014), and memory for visual stimuli endures over longer delays (Fagan, 1977; for review, see Rose, Feldman, & Jankowski, 2004). These predictable changes appear consistent across infant populations. For example, infants who were born preterm also show predictable developmental changes in gaze switching, look duration, and visual recognition, but at a delayed rate that can linger well into adolescence (Rose et al., 2012). If we can attain a theoretical understanding of how real-time processes create developmental change in these cognitive and behavioral systems, we can play on those real-time processes to push those systems along a positive developmental trajectory.

The three-layer model integrates second-to-second dynamics of looking behavior, encoding, and working memory formation with the longer timescale of long-term memory formation via the memory trace mechanism (Hebbian learning) described earlier. As illustrated in Fig. 3, Perone and Spencer (2013a) situated this model in a virtual world in which it was free to explore objects distributed over a dimension (e.g., several objects that differ in color), much like infants sitting and switching gaze among an array of objects. Periodically, one object was swapped out for a new one in order to provide the model experience with a variety of objects distributed along an entire dimension (i.e., many objects of different colors, such as blues, purples, reds, and oranges). While the model was exploring its virtual world, it was occasionally situated in a laboratory task, the "processing speed" task developed by Rose, Feldman, and Jankowski (2002). The purpose was to probe the influence of the history the model was accumulating over a series of real-time instances of fixating, encoding, and remembering objects on cognition and looking behavior as we measure them in the laboratory, that is, in a constrained task context in a cross-sectional fashion.

The Rose et al.'s (2002) processing speed task is based on the fact that infants look less at remembered items than novel items. Infants were presented with a pair of items, one designated as the familiar and the other as the novel, as shown in Fig. 4. On every trial, the novel item was replaced with a new item and the familiar remained the same, with the side of the display that contained the familiar item changing randomly across trials. Processing speed was defined as the number of trials it took for the infant to display a

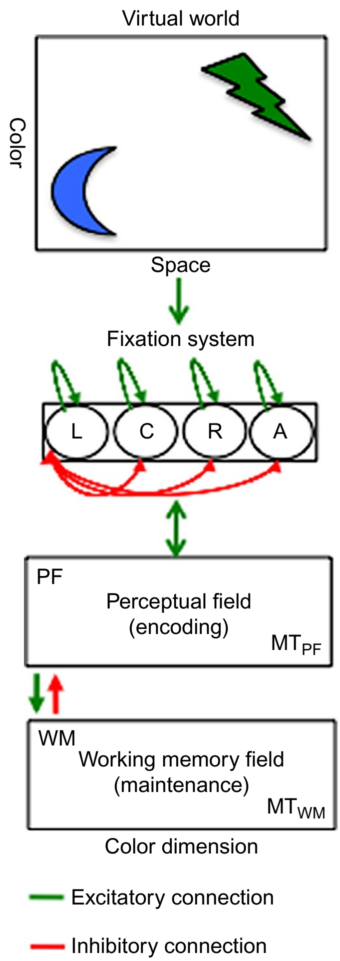

Fig. 3 DNF model architecture situated in the "virtual world" used by Perone and Spencer (2013a). At the *top* is a virtual world at which the model looks. The virtual world consists of two objects at *left* and *right* locations distributed over a continuous feature dimension (e.g., color). The presence of items at *left* and *right* locations biases the fixation system to look at those locations (see *green arrow* from space to fixation system). The fixation system interacts in a winner-take-all fashion such that fixating a location suppresses fixation to all other locations (see *red arrows* between nodes). Fixating a location acts like a perceptual gate into the cognitive system, which consists of a perceptual field (PF) and working memory (WM) field. PF and WM are reciprocally coupled to a shared layer of inhibitory interneurons (Inhib; not show). Activity in PF supports fixation (*green* bidirectional *arrow* between PF and fixation). Activity in WM suppresses PF via a strongly tuned connection from WM to Inhib (*red arrow* from WM to PF). Activity in PF and WM is influenced by activity in Hebbian layers, HLPF and HLWM, respectively, which accumulates over learning and facilitates encoding in PF and memory formation in WM. *Adapted from Perone, S., & Spencer, J. P. (2013a). Autonomous visual exploration creates developmental change in familiarity and novelty seeking behaviors.* Frontiers in Cognitive Science, 4*, 648. http://doi.org/10.3389/fpsyg.2013.00648.*

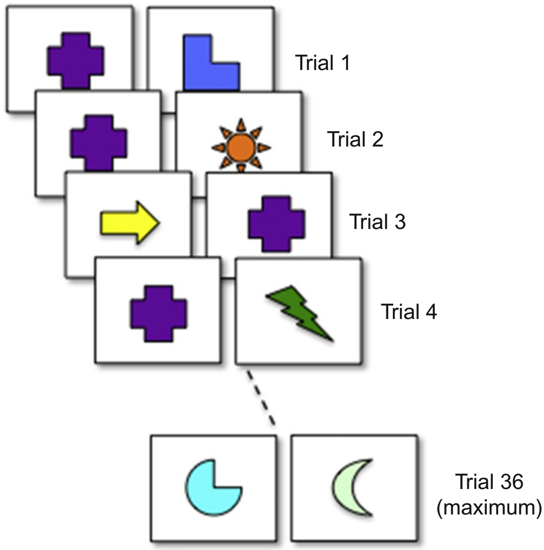

Fig. 4 Processing speed task developed by Rose et al. (2002). Infants were presented with a pair of different stimuli on each trial. Across trials, one stimulus remained unchanged (familiar) and one changed (novel). On each trial, infants were required to accumulate 4 s of looking. Infants met a learning criterion once they looked at the novel stimulus more than 55% of the time on the three consecutive trials or 36 trials had passed. There were 19 stimuli, one designated as the familiar and 18 designated as novel. If 18 trials had passed before infants met the criteria, the 18 novel stimuli were re-presented. *Adapted from Perone, S., & Spencer, J. P. (2013a). Autonomous visual exploration creates developmental change in familiarity and novelty seeking behaviors.* Frontiers in Cognitive Science, 4*, 648. http://doi.org/10.3389/fpsyg.2013.00648.*

reliable novelty preference (i.e., three consecutive trials in which infants looked at the novel item at least 55% of the time). With age, infants required fewer trials to meet this criterion. What did the DNF model do as it accumulated experience over "development"? It performed similarly to infants. As the DNF model accrued stronger memory traces over a dimension (e.g., color), the model more quickly processed objects sampled from that dimension. Why did this happen? Perone and Spencer (2013a) found that as the long-term memory traces built up via exploration of objects in the virtual world, the model formed working memory representations of the familiar item in the lab-based processing speed task more quickly. This highlights the reciprocal causality of dynamic systems: the real-time scale (i.e., fixating, encoding, and remembering objects) was structuring the developmental timescale (i.e., accumulation of memory traces) just as the developmental timescale constrained the real-time scale (i.e., the formation of working memory representations). This also highlights how the historical nature of systems enables them to create developmental change in themselves.

Rose et al. (2002) found that preterm infants exhibited a delayed developmental trajectory relative to full-term infants. Perone and Spencer (2013a) were able to capture this delay by simply initializing the DNF model with slightly weaker strength of the excitatory and inhibitory connections that governed the cognitive processes in the model. This preterm infant version of the model accumulated memory traces via exploration of the virtual world that were comparable in strength to the full-term infant model. However, the weaker connectivity of the preterm infant model led it to form working memory representations for familiar items more slowly than the full-term infant model did. Perone and Spencer tested whether a simple intervention might alter the developmental trajectory of the preterm infant model. Specifically, they situated an algorithmic "parent" in the virtual world with the preterm infant model. The role of the parent was to maintain the preterm infant model's gaze on the object it was looking at, much like a parent would tap or hold up an object to keep their baby interested in looking at it. Encouraging this type of parental behavior is a common component of early interventions for preterm infants (e.g., Landry, Smith, & Swank, 2006). This simple manipulation led the preterm infant model to accumulate very strong memory traces that in turn enabled it to form working memory representations more rapidly in the lab-based processing speed task. The preterm infant model now exhibited a developmental trajectory much like the full-term infant model. This set of simulations nicely showed that understanding the real-time processes of an historical system can be a powerful tool for practitioners and parents to help nudge development along a positive path. Such interventions could be greatly facilitated by a firm foundational appreciation of the link between the real-time processes and developmental change like that specified by the DNF model.

3. NONCOMPUTATIONAL APPLICATIONS OF SYSTEMS CONCEPTS

The preceding section showcased applications of DST to cognition and development using neural process models, but computational approaches only represent a small proportion of research conducted under the umbrella of DST. In this section, we highlight noncomputational applications of DST that embrace the complexity of cognition, behavior, and development. We selected three applications that have yielded unique insights using a variety of innovative methodologies. First, we review research examining the connection between motor and language development to illustrate the interdependency and inseparability of systems that are traditionally considered unrelated. Second, we describe the emergence of the shape bias in early word learning. This research illustrates nesting of timescales in developmental change and highlights the type of rigorous methodology used to apply DST to the study of development. Last, we discuss research demonstrating the importance of zooming in on development to understand developmental trajectories.

3.1 Coupled Motor and Language Systems

Systems approaches have often led to the discovery of nonobvious connections between systems, which in turn have led to a deep understanding of how the behavior of one system can propel development in another domain forward (see Spencer, Blumberg, et al., 2009). One excellent example is the connection between motor and language systems. Iverson (2010) proposed that language development should be viewed within the context of the body in which it develops. The motor system can provide children practice generating behaviors in the movement domain that mimic those in the linguistic domain. There is good evidence that motor movements and language are tightly coupled over development. Rhythmic motor behaviors (e.g., shaking) emerge at the same time as, or just precede, reduplicated babble—vocalizations that are organized into a rhythmic sequence, like "bababa" (e.g., Eilers et al., 1993). One possible connection is that rhythmic motor behaviors provide infants the opportunity to practice and master rhythmically organized behaviors. A collection of longitudinal studies have shown that shaking was low in prebabbling infants, increased as infants began to babble, and then declined when infants became experienced babblers (for review, see Iverson, 2010).

The motor system can also shape language by providing the child new opportunities to explore the environment and communicate with others, as illustrated by Walle and Campos (2014). Their first study utilized a longitudinal design that followed infants from 10 to 14 months of age, a time when infants in the United States typically transition from crawling to walking (Adolph, Tamis-LeMonda, & Karasik, 2010). Walle and Campos found that this transition in locomotor skill was associated with an increase in infants' receptive and expressive language. Their second study, using an age-held-constant design, showed that walking infants had larger vocabularies than same-aged crawling infants. They also observed same-aged crawling and walking infants in a free play session with caregivers and found that acting and communicating in the social environment predicted infants' language. For example, parents' vocalizations toward their infants and infants' own movements positively predicted receptive vocabulary, after controlling for locomotive status (i.e., crawler vs walker). Interestingly, they found an interaction between parents' vocalizations and locomotor status, such that greater vocalizations predicted receptive vocabulary only for walking infants. They also found an interaction between parental movement around the space and locomotor status, such that less parental movement predicted greater receptive vocabulary for walking infants. This finding may reflect the reorganization of the dyadic system, induced by the child learning to walk. For instance, parents may need to frequently communicate with their newly walking infant at greater distances as they explore the space. This can help the infant build a receptive vocabulary and free the parent from moving about the space to communicate.

Parladé and Iverson (2011) also investigated the link between motor and language development using DST concepts as a concrete guide to experimental design. These researchers were interested in transition points in vocabulary development. The premise of their research was that transition points provide a window into the processes of change. During transition points, systems become less stable as they reorganize. For this reason, Parladé and Iverson expected that the stable link between gesture, affect, and communication would temporarily become decoupled as children direct effort toward building their first vocabulary. The vocabulary spurt, a period during which children's vocabulary can double in as little as one month's time, typically occurs around 16–18 months of age in US English-speaking children. Parladé and Iverson examined the coupling between communicative behaviors (i.e., gestures, affect, vocalizations) during this transitional period. They expected a change in coordination among communicative behaviors during the vocabulary spurt, reasoning that language during this time is effortful, so coordination among systems would be disrupted. They identified children who exhibited a vocabulary spurt and examined their behavior before, during, and after their spurt in naturalistic interactions with caregivers and structured interactions with toys. Results showed that children who did vs did not go through a vocabulary spurt showed different developmental patterns in the coordination of communicative behaviors (e.g., gesturing and vocalizing close in time). Children who did not show a spurt showed a gradual increase in coordinated behaviors. For those children who did show a spurt, the coordination varied at this point, with a decrease in coordinated communication during the spurt relative to their own pre- and postspurt periods. These individual differences in developmental trajectories illustrate how systems interact and influence each other through time.

The literature examining how motor and language systems are connected highlights how dynamic systems can propel themselves forward. This might involve the production of rhythmic behaviors in the motor domain that bootstrap rhythmic behaviors in the language domain. This might involve emergent consequences of locomotion, such as communicating over a distance that can foster receptive vocabulary growth. This literature also highlights innovative methodologies, such as zooming in on transition points (cf. microgenetic method; Siegler & Crowley, 1991) and analyzing individual developmental trajectories in detail that can provide unique insights into the processes of change.

3.2 Shape Bias in Word Learning

The shape bias is a word-learning bias that young word learners exhibit in which they generalize new labels (e.g., ball) to novel objects that share the same shape (e.g., round) rather than other properties like color or material. This bias helps children rapidly acquire a vocabulary of count nouns, which are words that generally refer to categories organized by shape (e.g., apple, shoe, ball; see Samuelson & Smith, 1999). There is some debate about the origins of the shape bias. For example, Markson, Diesendruck, and Bloom (2008) proposed a shape-as-cue account that posits that the shape bias reflects children's explicit understanding that count nouns and object shape are a cue to object "kind," a concept that is independent of language experience. Samuelson and colleagues (e.g., Samuelson, 2002; Samuelson & Smith, 1999) have proposed an attentional learning account that is grounded in DST. Their research has demonstrated that the emergence of the shape bias reflects a history of word learning that creates change in and propels the language system forward. One of the key insights from Samuelson and colleagues' research is that the emergence of the shape bias depends on the structure of the early vocabulary. Among English-learners in the United States, the statistics of children's early vocabulary are typically dominated by nouns that refer to categories of solid objects organized by shape (e.g., ball, cup; Samuelson & Smith, 1999). A number of training studies have shown that the language system is open to external forces that alter vocabulary structure. For example, Samuelson (2002) taught young word learners (15- to 20-month-olds) 12 nouns from the natural statistics of the early vocabulary, which is dominated by solid objects in shape-based categories (e.g., shoe, ball, bucket). Relative to nontrained children, these children exhibited a precocious shape bias after only 9 weeks and, remarkably, continued rapid vocabulary growth 1 month after the training ended.

The acquisition of the shape bias also depends on the particular category exemplars children experience. Perry, Samuelson, Malloy, and Schiffer (2010) taught two groups of 18-month-old children the same set of 12 nouns, but manipulated the similarity among exemplars. For example, one group of children was taught the word "bucket" for three very different buckets (e.g., spherical, short cylindrical, tall cylindrical) and one group of children was taught the same word for three similar buckets (e.g., tall cylindrical). These two groups of children exhibited different word-learning trajectories. Children who were trained with more variable exemplars acquired a discriminating shape bias (i.e., generalizing differently for solid vs nonsolid items) and greater vocabulary growth than children who were trained with less variable examples of solid, shape-based categories.

The shape bias studies we reviewed are tied to several DST concepts. For example, the studies illustrate that the language system is open to variants in input (e.g., category exemplars), which can nudge the emergence of the shape bias for an individual child along a unique trajectory. The studies showed that the shape bias emerges from the accumulation of real-time word-learning experiences over time, and in this way exemplifies how an historical system can propel itself forward. The shape bias literature has also illustrated another important DST concept that the language system self-organizes in context. A classic example of the context dependency of a self-organizing system is the stepping reflex. Very young infants will lift their feet in alternation when held up with their feet touching a hard surface. Around 5 months of age, this reflex "disappears": infants no longer lift their legs when held upright, a change that had been explained as a developmental shift from reflexes to voluntary (cortical) control of movement. Thelen, Fisher, and Ridley-Johnson (1984) showed that the "stepping reflex" disappears as infants' legs gain fat and their muscles are not strong enough to lift their legs against the force of gravity. However, when infants are placed in a fish tank filled with water, their legs become buoyant and the stepping reflex reappears. Thelen et al. proposed that the appearance of stepping in the fish tank reflected the assembly of motor system components in context. Perry, Samuelson, and Burdinie (2014) showed that children's early word-learning biases similarly self-organize in context. In particular, when young word learners (16-month-olds) were situated in a high chair, they were more likely to generalize novel names by material than by shape. When at a table, by contrast, children showed no systematic biases. Why would this be so? Perry et al. (2014) proposed the intriguing idea that mealtime is a unique word-learning context in which children are exposed to many nonsolid substances with categories organized by material (e.g., applesauce, yogurt). Thus, the most relevant information for generalizing names differs based on context—a regularity that toddlers can learn to use for learning new words.

3.3 Sampling Development

The literatures on the coupling between language and motor development and the shape bias focus on the process of change. These literatures nicely highlight that a system's approach to understanding developmental change requires "zooming in" on the real-time processes that shape trajectories over the course of months and years. Adolph, Robinson, Young, and Gill-Alvarez (2008) argued that understanding the shape of trajectories and why they progress the way they do requires a unique methodology (see also Adolph & Robinson, 2011). Indeed, they propose that understanding such trajectories requires sampling behavior in a much more fine-grained fashion than is typical in developmental science. A good example is physical growth. Observing growth yearly, monthly, daily, or hourly tells us something very different about growth trajectories, as well as the process that leads children to grow. Growth is usually described as spurts during infancy and adolescence. When measured every day, however, growth appears to be more episodic throughout childhood, with children growing quite a bit in a single day interspersed with longer periods without growth. Large temporal gaps in sampling, such as on an annual basis, artificially make growth appear smooth and continuous when it is not.

Sampling development frequently is critically important for the application of DST to development and can provide a powerful window into individual trajectories. Adolph et al. (2008) demonstrated this in a study on motor skill acquisition during infancy. They asked parents to record daily observations of their infants' motor behavior (32 gross motor and balance skills) for several months. When mapping trajectories using daily data, the key finding was that infants rarely exhibited stage-like transitions, for instance, a period of never walking followed by a period of always walking.

Stage-like transitions were only observed about 15% of the time across all infants and skills. Instead, infants typically went through periods of variability in which they exhibited motor skills on some days and not others, vacillating through time as they acquired the skill. Sampling periodically from the daily observations, Adolph et al. could compare the trajectories implied by different rates of sampling using the same infants' data. Specifically, when sampled weekly, the percentage of transitions that appeared stage-like increased to about 50%, and when sampled monthly it increased to about 90%. Furthermore, not only did the less frequent sampling rate make skill transitions appear more stage-like than the more frequent sampling rate, the estimated age of acquisition was delayed with less frequent rates of sampling. Thus, both the timing and nature of skill transitions appeared different based on sampling rates, and these differences may lead theorists to propose different underlying mechanisms of change.

One of the most intriguing findings from the daily diaries was that infants exhibited about 13 transitions either way (i.e., from not showing a skill to showing it, or from showing a skill to not) for each motor skill. From a DST perspective, such variability arises from the interaction among components that make up the individual infant organizing in a new way once, twice, and so on, creating a new attractor state for the system to organize around. Entering an attractor state creates a history that, in turn, biases the system to reenter that state at a future point in time. Eventually, this pattern of organization will become a stable state that is the dominant behavior (see Spencer & Perone, 2008). The application of Adolph et al.'s (2008) methodology to other domains, such as cognition, may provide equally unique insights into what sources may move development along the trajectory it travels.

4. MOVING DYNAMIC SYSTEMS THEORY FORWARD

The goal of the current chapter was to illustrate the application of DST concepts to cognitive and behavioral development. DST emerged in developmental science in the early 1990s. In 1994, an issue of the *Journal of Experimental Child Psychology* focused on dynamic modeling of cognitive development, which stressed the computational application of the ideas embodied in DST. A quote from Bogartz (1994) regarding the future of DST stands out as particularly apropos in the context of our current review:

> *On the basis of history, current proclivities of active researchers, and current quantitative training of psychology students, my bet would have to be that this approach will probably fade from the scene or at best remain a little island of activity restricted to a small group of interested parties. (This is the kind of remark that gets quoted and snickered at 20 years later when the approach is flourishing) (p. 314).*

In developmental science, DST may currently be the island Bogartz predicted. Indeed, Howe and Lewis (2005) stated that "dynamic systems approaches to development remain a clear minority" (p. 250) and our survey of the literature more than a decade later reconfirmed this point. Although DST is not flourishing in the way we would like to see in the 20 years since Bogartz's comments on the application of this approach, neither has it faded from the scene. Our review shows that there are many applications of DST, suggesting growth along a trajectory that we believe is poised to continue upward.

We recognize that there are still significant barriers that stand in the way of DST becoming more widely applied to developmental science. These barriers must be overcome in order to go beyond the metaphorical chain of islands we have described here. We have identified four such barriers. First, as Bogartz (1994) so keenly noted, current (and prior) training of students does not equip them to handle the computational rigor of dynamic modeling. These computational demands include explicit simulation of cognitive processes and behavior, as we outlined in the modeling section earlier, but also sophisticated analytic tools that describe the dynamics of behavior via analysis of various time series data (e.g., recurrence quantification analysis). A deep discussion of such analytic methods is beyond the scope of the current chapter, but we want to highlight that methods are available to analyze coordination across levels (e.g., behavioral, cognitive, physiological) within individuals (e.g., van Orden, Holden, & Turvey, 2005), between conversation partners (e.g., Richardson, Dale, & Kirkham, 2007), or even among groups participating in social rituals (Konvalinka et al., 2011). These tools provide a different level of analysis than typical methods that treat the individual as the fundamental unit of measure. To our knowledge, these analytic tools have not been applied to development but would likely provide valuable insights into development as a dynamic system. Until such methods are taught as part of a typical curriculum in psychology or developmental science, their application will remain a narrow specialization. A recent increase in the resources available for scholars to learn different computational techniques is promising. This includes Schöner et al.'s

(2015) primer, workshops, and summer schools to learn DNF modeling, or workshops, courses, and web books in nonlinear methods offered by the University of Cincinnati and the University of Connecticut.

Second, the application of the DST framework requires rethinking the very nature of human thought, behavior, and development relative to our theoretical predecessors. Most psychology researchers have been trained (implicitly or explicitly) to seek single-cause explanations for behavior, or assume that multiple causal factors will interact linearly. The empirical paradigms taught in psychological science, in which we seek to control whatever factors we can and/or use random assignment to try to isolate the contribution of a single factor, are inherently contrary to the notion of multicausality. Knowing that human behavior is determined by the interaction of multiple factors (some of which combine nonlinearly) should lead us away from depending solely on these methods for drawing inferences and making predictions. This is not to say such studies have no place in psychological science—by analogy, the science of physics has benefitted from studying artificial environments like a vacuum—but we must be mindful that these approaches are removing meaningful variance by design, and temper our generalizations accordingly.

Third, a related limitation in the typical psychological perspective is the notion that only closely related experiences and behaviors may be "relevant" to the behavior of interest (see Spencer, Blumberg, et al., 2009 for discussion). The earlier examples of motor and language development provide a clear demonstration of how broadly relevant experience can be: how infants move their bodies through space and time influences what they hear (as well as what they see; Kretch, Franchak, & Adolph, 2014), which affords and elicits different opportunities for learning. A striking example of the need to consider learning in the context of the body comes from the groundbreaking studies of toddlers' visual perspective during naturalistic interactions with parents. Smith, Yu, and colleagues used head-mounted cameras to capture the view of objects by both the parent and toddler as they played with and talked about objects (e.g., Yu & Smith, 2012). Although the view from the parents' perspectives appeared unstructured for the purpose of word learning, analysis of parents' actions, toddlers' views, and the timing of naming events showed a great reduction in ambiguity: because toddlers' arms are short, when they hold objects in their hands, the proximity to their eyes makes the held object take up nearly the entire view. This example illustrates that a dimension that seems entirely irrelevant to language (body size) provides critical structure in the moment of learning.

Last, it is essential for researchers to understand behavior across timescales. We cannot explain how behavior changes over development without explaining how behavior emerges in the moment of a task. As our examples have illustrated, a careful analysis of the structure provided from the task context (as in the studies of visual working memory capacity) and an individual's history within and beyond the task (as in studies on the shape bias) can provide insights that are not apparent from theories that neglect these details. Although we believe this attention to task details is most transparently accomplished through computational modeling, such approaches are not strictly necessary. Careful analysis of what abilities are minimally required to perform a task can provide new insights into contributions to change (see, e.g., analysis of the A-not-B task by Smith et al., 1999).

In conclusion, adopting a DST approach to conducting developmental research is difficult, but ultimately worth the effort because it can provide a more complete explanation of how behavior emerges across task contexts over development. In the three decades since Fogel and Thelen (1987) introduced these ideas as a way to understand development, and especially since Thelen and Smith (1994) advocated for the broad application to the fields of cognitive and developmental psychology, we can chart remarkable growth in the appreciation of this perspective. Through our compilation and explanation of the range of applications reviewed, we hope to pave the way for continued expansion of these ideas into new and exciting frontiers in psychological science.

REFERENCES

Adolph, K. E., & Robinson, S. R. (2011). Sampling development. *Journal of Cognition and Development*, *12*(4), 411–423. http://doi.org/10.1080/15248372.2011.608190.

Adolph, K. E., Robinson, S. R., Young, J. W., & Gill-Alvarez, F. (2008). What is the shape of developmental change? *Psychological Review*, *115*(3), 527–543. http://doi.org/10.1037/0033-295X.115.3.527.

Adolph, K. E., Tamis-LeMonda, C. S., & Karasik, L. B. (2010). Motor skills. In M. H. Bornstein (Ed.), *Handbook of cultural developmental science* (pp. 61–88). New York: Psychology Press.

Alloway, T. P., Gathercole, S. E., Willis, C., & Adams, A.-M. (2004). A structural analysis of working memory and related cognitive skills in young children. *Journal of Experimental Child Psychology*, *87*, 85–106.

Amari, S. (1977). Dynamics of pattern formation in lateral-inhibition type neural fields. *Biological Cybernetics*, *27*, 77–87.

Baddeley, A. D. (1986). *Working memory*. Oxford: Oxford University Press.

Baillargeon, R. (1987). Object permanence in 3.5- and 4.5-month-old infants. *Developmental Psychology*, *23*, 655–664.

Bogartz, R. S. (1994). The future of dynamic systems models in developmental psychology in the light of the past. *Journal of Experimental Child Psychology*, *58*(2), 289–319. http://doi.org/10.1006/jecp.1994.1036.

Brannon, E. M., Suanda, S., & Libertus, K. (2007). Temporal discrimination increases in precision over development and parallels the development of numerosity discrimination. *Developmental Science*, *10*(6), 770–777. http://doi.org/10.1111/j.1467-7687.2007.00635.x.

Cashon, C. H., & Cohen, L. B. (2000). Eight-month-old infants' perception of possible and impossible events. *Infancy*, *1*(4), 429–446. http://doi.org/10.1207/S15327078IN0104_4.

Clearfield, M. W., Dineva, E., Smith, L. B., Diedrich, F. J., & Thelen, E. (2009). Cue salience and infant perseverative reaching: Tests of the dynamic field theory. *Developmental Science*, *12*, 26–40.

Clearfield, M. W., Smith, L. B., Diedrich, F. J., & Thelen, E. (2006). Young infants reach correctly on the A-not-B task: On the development of stability and perseveration. *Infant Behavior & Development*, *29*(3), 435–444.

Colombo, J., & Mitchell, D. W. (1990). Individual differences in early visual attention: Fixation time and information processing. In J. Colombo & J. Fagen (Eds.), *Individual differences in infancy: Reliability, stability, and prediction* (pp. 193–227). Hillsdale, NJ: Lawrence Erlbaum.

Cowan, N. (2007). What infants can tell us about working memory development. In L. M. Oakes & P. J. Bauer (Eds.), *Short- and long-term memory in infancy and early childhood: Taking the first steps toward remembering* (pp. 126–152). New York: Oxford University Press.

Cowan, N., Fristoe, N. M., Elliott, E. M., Brunner, R. P., & Saults, J. S. (2006). Scope of attention, control of attention, and intelligence in children and adults. *Memory & Cognition*, *34*(8), 1754–1768. http://doi.org/10.3758/BF03195936.

Diamond, A. (1985). Development of the ability to use recall to guide action, as indicated by infants' performance on AB. *Child Development*, *56*, 868–883.

Diedrich, F. J., Highlands, T., Thelen, E., & Smith, L. B. (2001). The role of target distinctiveness in infant perseverative reaching errors. *Journal of Experimental Child Psychology*, *78*, 263–290.

Diedrich, F. J., Thelen, E., Smith, L. B., & Corbetta, D. (2000). Motor memory is a factor in infant perseverative errors. *Developmental Science*, *3*, 479–494.

Eilers, R. E., Oller, D. K., Levine, S., Basinger, D., Lynch, M. P., & Urbano, R. (1993). The role of prematurity and socioeconomic status in the onset of canonical babbling in infants. *Infant Behavior and Development*, *16*(3), 297–315. http://doi.org/10.1016/0163-6383(93)80037-9.

Erlhagen, W., & Schöner, G. (2002). Dynamic field theory of movement preparation. *Psychological Review*, *109*, 545–572.

Fagan, J. F. (1970). Memory in the infant. *Journal of Experimental Child Psychology*, *9*(2), 217–226.

Fagan, J. F. (1977). Infant recognition memory: Studies in forgetting. *Child Development*, *48*(1), 68. http://doi.org/10.2307/1128883.

Fogel, A. (2011). Theoretical and applied dynamic systems research in developmental science: Dynamic systems research. *Child Development Perspectives*, *5*(4), 267–272. http://doi.org/10.1111/j.1750-8606.2011.00174.x.

Fogel, A., & Thelen, E. (1987). Development of early expressive and communicative action: Reinterpreting the evidence from a dynamic systems perspective. *Developmental Psychology*, *23*(6), 747–761. http://doi.org/10.1037/0012-1649.23.6.747.

Gratch, G., Appel, K. J., Evans, W. F., LeCompte, G. K., & Wright, N. A. (1974). Piaget's stage IV object concept error: Evidence of forgetting or object conception? *Child Development*, *45*(1), 71. http://doi.org/10.2307/1127751.

Haith, M. M. (1998). Who put the cog in infant cognition? Is rich interpretation too costly? *Infant Behavior and Development*, *21*(2), 167–179. http://doi.org/10.1016/S0163-6383(98)90001-7.

Hollenstein, T. (2011). Twenty years of dynamic systems approaches to development: Significant contributions, challenges, and future directions: 20 Years of dynamic systems. *Child Development Perspectives*, *5*(4), 256–259. http://doi.org/10.1111/j.1750-8606.2011.00210.x.

Howe, M. L., & Lewis, M. D. (2005). The importance of dynamic systems approaches for understanding development. *Developmental Review*, *25*(3–4), 247–251. http://doi.org/10.1016/j.dr.2005.09.002.

Hund, A. M., & Spencer, J. P. (2003). Developmental changes in the relative weighting of geometric and experience-dependent location cues. *Journal of Cognition and Development*, *4*(1), 3–38.

Iverson, J. M. (2010). Developing language in a developing body: The relationship between motor development and language development. *Journal of Child Language*, *37*(2), 229. http://doi.org/10.1017/S0305000909990432.

Johnson, J. S., & Simmering, V. R. (2015). Integrating perception and working memory in a three-layer dynamic field architecture. In G. Schöner, J. P. Spencer, & The DFT Research Group (Eds.), *Dynamic thinking: A primer on dynamic field theory* (pp. 151–168). New York: Oxford University Press.

Johnson, J. S., Simmering, V. R., & Buss, A. T. (2014). Beyond slots and resources: Grounding cognitive concepts in neural dynamics. *Attention, Perception, & Psychophysics*, *76*(6), 1630–1654. http://doi.org/10.3758/s13414-013-0596-9.

Konvalinka, I., Xygalatas, D., Bulbulia, J., Schjødt, U., Jegindø, E.-M., Wallot, S., … Roepstorff, A. (2011). Synchronized arousal between performers and related spectators in a fire-walking ritual. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(20), 8514–8519. http://doi.org/10.1073/pnas.1016955108.

Kretch, K. S., Franchak, J. M., & Adolph, K. E. (2014). Crawling and walking infants see the world differently. *Child Development*, *85*(4), 1503–1518. http://doi.org/10.1111/cdev.12206.

Landry, S. H., Smith, K. E., & Swank, P. R. (2006). Responsive parenting: Establishing early foundations for social, communication, and independent problem-solving skills. *Developmental Psychology*, *42*(4), 627–642.

Lewis, M. D. (2011). Dynamic systems approaches: Cool enough? Hot enough? Dynamic systems approaches. *Child Development Perspectives*, *5*(4), 279–285. http://doi.org/10.1111/j.1750-8606.2011.00190.x.

Lipinski, J., Simmering, V. R., Johnson, J. S., & Spencer, J. P. (2010). The role of experience in location estimation: Target distributions shift location memory biases. *Cognition*, *115*, 147–153.

Lipinski, J., Spencer, J. P., & Samuelson, L. K. (2010). Biased feedback in spatial recall yields a violation of delta rule learning. *Psychonomic Bulletin & Review*, *17*(4), 581–588.

Logie, R. H. (1995). *Visual-spatial working memory*. Hove, UK: Erlbaum.

Marcovitch, S., & Zelazo, P. D. (1999). The A-not-B error: Results from a logistic meta-analysis. *Child Development*, *70*, 1297–1313.

Markson, L., Diesendruck, G., & Bloom, P. (2008). The shape of thought. *Developmental Science*, *11*(2), 204–208. http://doi.org/10.1111/j.1467-7687.2007.00666.x.

Munakata, Y. (1998). Infant perseveration and implications for object permanence theories: A PDP model of the AB task. *Developmental Science*, *1*(2), 161–184.

Oakes, L. M., Baumgartner, H. A., Barrett, F. S., Messenger, I. M., & Luck, S. J. (2013). Developmental changes in visual short-term memory in infancy: Evidence from eye-tracking. *Frontiers in Psychology*, *4*, 697. http://doi.org/10.3389/fpsyg.2013.00697.

Oakes, L. M., Messenger, I. M., Ross-Sheehy, S., & Luck, S. J. (2009). New evidence for rapid development of color-location binding in infants' visual short-term memory. *Visual Cognition*, *17*, 67–82.
Oakes, L. M., Ross-Sheehy, S., & Luck, S. J. (2006). Rapid development of feature binding in visual short-term memory. *Psychological Science*, *17*(9), 781–787.
Parladé, M. V., & Iverson, J. M. (2011). The interplay between language, gesture, and affect during communicative transition: A dynamic systems approach. *Developmental Psychology*, *47*(3), 820–833. http://doi.org/10.1037/a0021811.
Pashler, H. (1988). Familiarity and visual change detection. *Perception and Psychophysics*, *44*, 369–378. http://doi.org/10.3758/BF03210419.
Perone, S., & Ambrose, J. P. (2015). A process view of learning and development in an autonomous exploratory system. In G. Schöner, J. P. Spencer, & The DFT Research Group (Eds.), *Dynamic thinking: A primer on dynamic field theory* (pp. 271–296). New York: Oxford University Press.
Perone, S., Simmering, V. R., & Spencer, J. P. (2011). Stronger neural dynamics capture changes in infants' visual working memory capacity over development. *Developmental Science*, *14*, 1379–1392. http://doi.org/10.1111/j.1467-7687.2011.01083.x.
Perone, S., & Spencer, J. P. (2013a). Autonomous visual exploration creates developmental change in familiarity and novelty seeking behaviors. *Frontiers in Psychology*, *4*, 648. http://doi.org/10.3389/fpsyg.2013.00648.
Perone, S., & Spencer, J. P. (2013b). Autonomy in action: Linking the act of looking to memory formation in infancy via dynamic neural fields. *Cognitive Science*, *37*, 1–60. http://doi.org/10.1111/cogs.12010.
Perone, S., & Spencer, J. P. (2014). The co-development of looking dynamics and discrimination performance. *Developmental Psychology*, *50*(3), 837–852. http://doi.org/10.1037/a0034137.
Perry, L. K., Samuelson, L. K., & Burdinie, J. B. (2014). Highchair philosophers: The impact of seating context-dependent exploration on children's naming biases. *Developmental Science*, *17*(5), 757–765. http://doi.org/10.1111/desc.12147.
Perry, L. K., Samuelson, L. K., Malloy, L. M., & Schiffer, R. N. (2010). Learn locally, think globally: Exemplar variability supports higher-order generalization and word learning. *Psychological Science*, *21*(12), 1894–1902. http://doi.org/10.1177/0956797610389189.
Piaget, J. (1954). *The construction of reality in the child*. New York: Basic Books.
Richardson, D. C., Dale, R., & Kirkham, N. Z. (2007). The art of conversation is coordination common ground and the coupling of eye movements during dialogue. *Psychological Science*, *18*(5), 407–413. http://doi.org/10.1111/j.1467-9280.2007.01914.x.
Riggs, K. J., McTaggart, J., Simpson, A., & Freeman, R. P. J. (2006). Changes in the capacity of visual working memory in 5- to 10-year-olds. *Journal of Experimental Child Psychology*, *95*, 18–26. http://doi.org/10.1016/j.jecp.2006.03.009.
Rivera, S. M., Wakeley, A., & Langer, J. (1999). The drawbridge phenomenon: Representational reasoning or perceptual preference? *Developmental Psychology*, *35*(2), 427–435.
Rose, S. A., Feldman, J. F., & Jankowski, J. J. (2001). Attention and recognition memory in the 1st year of life: A longitudinal study of preterm and full-term infants. *Developmental Psychology*, *37*(1), 135–151. http://doi.org/10.1037/0012-1649.37.1.135.
Rose, S. A., Feldman, J. F., & Jankowski, J. J. (2002). Processing speed in the 1st year of life: A longitudinal study of preterm and full-term infants. *Developmental Psychology*, *38*, 895–902. http://doi.org/10.1037/0012-1649.38.6.895.
Rose, S. A., Feldman, J. F., & Jankowski, J. J. (2004). Infant visual recognition memory. *Developmental Review*, *24*, 74–100.
Rose, S. A., Feldman, J. F., & Jankowski, J. J. (2012). Implications of infant cognition for executive functions at age 11. *Psychological Science*, *23*(11), 1345–1355. http://doi.org/10.1177/0956797612444902.

Ross-Sheehy, S., Oakes, L. M., & Luck, S. J. (2003). The development of visual short-term memory capacity in infants. *Child Development*, *74*, 1807–1822.

Samuelson, L. K. (2002). Statistical regularities in vocabulary guide language acquisition in connectionist models and 15-20-month-olds. *Developmental Psychology*, *38*(6), 1016–1037. http://doi.org/10.1037/0012-1649.38.6.1016.

Samuelson, L. K., Schutte, A. R., & Horst, J. S. (2009). The dynamic nature of knowledge: Insights from a dynamic field model of children's novel noun generalization. *Cognition*, *110*, 322–345. http://doi.org/10.1016/j.cognition.2008.10.017.

Samuelson, L. K., & Smith, L. B. (1999). Early noun vocabularies: Do ontology, category structure and syntax correspond? *Cognition*, *73*(1), 1–33. http://doi.org/10.1016/S0010-0277(99)00034-7.

Schöner, G., Spencer, J. P., & The DFT Research Group. (2015). *Dynamic thinking: A primer on dynamic field theory*. New York: Oxford University Press.

Schöner, G., & Thelen, E. (2006). Using dynamic field theory to rethink infant habituation. *Psychological Review*, *113*(2), 273–299.

Schutte, A. R., & Spencer, J. P. (2002). Generalizing the dynamic field theory of the A-not-B error beyond infancy: Three-year-olds' delay- and experience-dependent location memory biases. *Child Development*, *73*, 377–404.

Schutte, A. R., Spencer, J. P., & Schöner, G. (2003). Testing the dynamic field theory: Working memory for locations becomes more spatially precise over development. *Child Development*, *74*(5), 1393–1417.

Siegler, R. S., & Crowley, K. (1991). The microgenetic method: A direct means for studying cognitive development. *American Psychologist*, *46*(6), 606–620. http://doi.org/10.1037/0003-066X.46.6.606.

Simmering, V. R. (2012). The development of visual working memory capacity in early childhood. *Journal of Experimental Child Psychology*, *111*, 695–707. http://doi.org/10.1016/j.jecp.2011.10.007.

Simmering, V. R. (2016). Working memory capacity in context: Modeling dynamic processes of behavior, memory, and development. *Monographs of the Society for Research in Child Development*, *81*, 1–168. http://doi.org/10.1111/mono.12202.

Simmering, V. R., Miller, H. E., & Bohache, K. (2015). Different developmental trajectories across feature types support a dynamic field model of visual working memory development. *Attention, Perception, & Psychophysics*, 77(4), 1170–1188. http://doi.org/10.3758/s13414-015-0832-6.

Simmering, V. R., & Perone, S. (2013). Working memory capacity as a dynamic process. *Frontiers in Psychology*, *3*, 567. http://doi.org/10.3389/fpsyg.2012.00567.

Simmering, V. R., Schutte, A. R., & Spencer, J. P. (2008). Generalizing the dynamic field theory of spatial cognition across real and developmental time scales. *Brain Research*, *1202*, 68–86. http://doi.org/10.1016/j.brainres.2007.06.081.

Simmering, V. R., & Spencer, J. P. (2007). Carving up space at imaginary joints: Can people mentally impose spatial category boundaries? *Journal of Experimental Psychology Human Perception and Performance*. *33*, 871–894. http://doi.org/10.1037/0096-1523.33.4.871.

Smith, L. B., & Thelen, E. (2003). Development as a dynamic system. *Trends in Cognitive Sciences*, 7(8), 343–348. http://doi.org/10.1016/S1364-6613(03)00156-6.

Smith, L. B., Thelen, E., Titzer, R., & McLin, D. (1999). Knowing in the context of acting: The task dynamics of the A-not-B error. *Psychological Review*, *106*, 235–260.

Spelke, E. S. (1985). Perception of unity, persistence, and identity: Thoughts on infants' conceptions of objects. In J. Mehler & R. Fox (Eds.), *Neonate cognition: Beyond the blooming buzzing confusion* (pp. 89–113): Lawrence Erlbaum.

Spencer, J. P., Blumberg, M. S., McMurray, B., Robinson, S. R., Samuelson, L. K., & Tomblin, J. B. (2009). Short arms and talking eggs: Why we should no longer abide the nativist-empiricist debate. *Child Development Perspectives*, *3*(2), 79–87. http://doi.org/10.1111/j.1750-8606.2009.00081.x.

Spencer, J. P., Clearfield, M., Corbetta, D., Ulrich, B., Buchanan, P., & Schöner, G. (2006). Moving toward a grand theory of development: In memory of Esther Thelen. *Child Development*, *77*, 1521–1538.

Spencer, J. P., Dineva, E., & Smith, L. B. (2009). Comment on "Infants' perseverative search errors are induced by pragmatic misinterpretation". *Science*, *325*(5948), 1624. http://doi.org/10.1126/science.1172759.

Spencer, J. P., & Hund, A. M. (2002). Prototypes and particulars: Geometric and experience-dependent spatial categories. *Journal of Experimental Psychology. General*, *131*, 16–37.

Spencer, J. P., & Hund, A. M. (2003). Developmental continuity in the processes that underlie spatial recall. *Cognitive Psychology*, *47*(4), 432–480.

Spencer, J. P., & Perone, S. (2008). Defending qualitative change: The view from dynamical systems theory. *Child Development*, *79*(6), 1639–1647. http://doi.org/10.1111/j.1467-8624.2008.01214.x.

Spencer, J. P., Perone, S., & Buss, A. T. (2011). Twenty years and going strong: A dynamic systems revolution in motor and cognitive development. *Child Development Perspectives*, *5*(4), 260–266.

Spencer, J. P., & Schöner, G. (2003). Bridging the representational gap in the dynamical systems approach to development. *Developmental Science*, *6*, 392–412.

Spencer, J. P., & Schutte, A. R. (2004). Unifying representations and responses: Perseverative biases arise from a single behavioral system. *Psychological Science*, *15*(3), 187–193.

Spencer, J. P., Simmering, V. R., & Schutte, A. R. (2006). Toward a formal theory of flexible spatial behavior: Geometric category biases generalize across pointing and verbal response types. *Journal of Experimental Psychology. Human Perception and Performance*, *32*, 473–490.

Spencer, J. P., Simmering, V. R., Schutte, A. R., & Schöner, G. (2007). What does theoretical neuroscience have to offer the study of behavioral development? Insights from a dynamic field theory of spatial cognition. In J. M. Plumert & J. P. Spencer (Eds.), *The emerging spatial mind* (pp. 320–361). New York: Oxford University Press.

Spencer, J. P., Smith, L. B., & Thelen, E. (2001). Tests of a dynamic systems account of the A-not-B error: The influence of prior experience on the spatial memory abilities of 2-year-olds. *Child Development*, *72*, 1327–1346.

Thelen, E., Fisher, D. M., & Ridley-Johnson, R. (1984). The relationship between physical growth and a newborn reflex. *Infant Behavior & Development*, *7*, 479–493.

Thelen, E., Schöner, G., Scheier, C., & Smith, L. B. (2001). The dynamics of embodiment: A field theory of infant perseverative reaching. *Behavioral and Brain Sciences*, *24*, 1–86.

Thelen, E., & Smith, L. B. (1994). *A dynamic systems approach to the development of cognition and action*. Cambridge: MIT Press.

Topál, J., Gergely, G., Miklósi, A., Erdőhegyi, A., & Csibra, G. (2008). Infants' perseverative search errors are induced by pragmatic misinterpretation. *Science*, *321*(5897), 1831–1834. http://doi.org/10.1126/science.1161437.

Topál, J., Tóth, M., Gergely, G., & Csibra, G. (2009). Response to comment on "Infants' perseverative search errors are induced by pragmatic misinterpretation". *Science*, *325*(5948), 1624. http://doi.org/10.1126/science.1173024.

Tronick, E., Als, H., Adamson, L., Wise, S., & Brazelton, T. B. (1978). The infant's response to entrapment between contradictory messages in face-to-face interaction. *Journal of the American Academy of Child Psychiatry*, *17*(1), 1–13. http://doi.org/10.1016/S0002-7138(09)62273-1.

van Geert, P. (2011). The contribution of complex dynamic systems to development: Contribution of complex dynamic systems to development. *Child Development Perspectives*, *5*(4), 273–278. http://doi.org/10.1111/j.1750-8606.2011.00197.x.

van Geert, P., & Steenbeek, H. (2005). Explaining after by before: Basic aspects of a dynamic systems approach to the study of development. *Developmental Review*, *25*(3–4), 408–442. http://doi.org/10.1016/j.dr.2005.10.003.

van Orden, G. C., Holden, J. G., & Turvey, M. T. (2005). Human cognition and 1/f scaling. *Journal of Experimental Psychology. General*, *134*(1), 117–123. http://doi.org/10.1037/0096-3445.134.1.117.

Vogel, E. K., Woodman, G. F., & Luck, S. J. (2001). Storage of features, conjunctions, and objects in visual working memory. *Journal of Experimental Psychology Human Perception and Performance*, *27*, 92–114.

Walle, E. A., & Campos, J. J. (2014). Infant language development is related to the acquisition of walking. *Developmental Psychology*, *50*(2), 336–348. http://doi.org/10.1037/a0033238.

Wilson, H. R., & Cowan, J. D. (1972). Excitatory and inhibitory interactions in localized populations of model neurons. *Biophysical Journal*, *12*, 1–24.

Witherington, D. C. (2007). The dynamic systems approach as metatheory for developmental psychology. *Human Development*, *50*(2–3), 127–153. http://doi.org/10.1159/000100943.

Witherington, D. C., & Margett, T. E. (2011). How conceptually unified is the dynamic systems approach to the study of psychological development? Conceptual unification in dynamic systems. *Child Development Perspectives*, *5*(4), 286–290. http://doi.org/10.1111/j.1750-8606.2011.00211.x.

Yu, C., & Smith, L. B. (2012). Embodied attention and word learning by toddlers. *Cognition*, *125*(2), 244–262. http://doi.org/http://dx.doi.org/10.1016/j.cognition.2012.06.016.