Developmental Systems Science: Exploring the Application of Systems Science Methods to Developmental Science Questions

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Abstract

Developmental science theorists fully acknowledge the wide array of complex interactions between biology, behavior, and environment that together give rise to development. However, despite this conceptual understanding of development as a system, developmental science has not fully applied analytic methods commensurate with this systems perspective. This paper provides a brief introduction to systems science, an approach to problem-solving that involves the use of methods especially equipped to handle complex relationships and their evolution over time. Moreover, we provide a rationale for why and how these methods can serve the needs of the developmental science research community. A variety of developmental science theories are reviewed and the need for systems science methodologies is demonstrated. This is followed by an abridged primer on systems science terminology and concepts, with specific attention to how these concepts relate to similar concepts in developmental science. Finally, an illustrative example is presented to demonstrate the utility of systems science methodologies. We hope that this article inspires developmental scientists to learn more about systems science methodologies and to begin to use them in their work.

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Developmental science is concerned with the study of changes that occur in human beings over the course of the life span. By its very nature, developmental science is concerned with the study of dynamically complex problems, because human development occurs over time and simultaneously in a variety of coupled dimensions. Understanding this complexity is one of the fundamental challenges of developmental science, and one that has not yet been fully met. Contributing to this state of affairs is that, to date, developmental science has not heavily invested in the use of methodologies that are expressly designed to offer insight into complex systems.

Thus, developmental science as a field is in need of new methodological tools to integrate large bodies of existing research at different levels of analysis and to address the complexity inherent in problems that develop and change across the life span. Systems science methodologies are well suited to such endeavors, but have yet to be harnessed to their full potential by developmental scientists. The purpose of this article and special issue is to increase awareness of systems science methodologies among developmental scientists and to encourage investigators to consider exploring the potential of systems science methodologies for addressing questions and problems in the purview of developmental science.

We begin with a discussion of the current state of the field of developmental science, focusing in particular on the developmental systems perspective as a theoretical approach that is well suited to exploration and study using systems science methodologies. This presentation is followed by an introduction to systems science methodologies and concepts and a demonstration of how the concepts and tools of systems science may be particularly relevant for developmental science questions. Finally, using an example from system dynamics, we illustrate how these systems science concepts and methods can be applied in the context of developmental science

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research questions. The subsequent papers in this volume focus on one of three featured systems science methodologies and provide an example of the specified methodology applied to a developmental question. See Osgood, et al. (this volume) for an example of system dynamics, Orr and Evans (this volume) for an example of agent-based modeling, and Okamoto, et al. (this volume) for an example of network analysis.

Key Concepts from the Developmental Systems Perspective

The notion of a systems approach to development is far from novel as is evidenced by theoretical work in areas such as bioecological systems theory (Bronfenbrenner & Morris, 2006), developmental systems theory (Ford & Lerner, 1992), probabilistic epigenesis (Gottleib, 1992, 1998; Gottlieb, Wahlsten, & Lickliter, 2006), dynamic systems theory (Thelen & Smith, 2006), and holistic person-context interaction theory (Magnusson & Stattin, 2006). These theoretical approaches share many commonalities and as a group can be considered part of the relational, *developmental systems perspective* at the cutting edge of *developmental science* (Lerner, 2006; Overton, 2010). The study of human development initially began as a discipline with a specific focus on the biological and psychological origins of development and has evolved into multidisciplinary approaches that explore variables from the biological to the cultural and historical levels (Lerner, 2006). The developmental systems perspective arose, in large part, as a response to the Cartesian dichotomies that defined the study of human development in terms of nature versus nurture, continuity versus discontinuity, and biology versus society (Lerner, 2002; Overton, 2010).

The specific focus of each developmental systems theory varies slightly; however, there are some common underlying themes that make them amenable to study with systems science methodologies, including: (1) development occurs within a multi-level holistic system, (2)

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development is temporal and occurs at multiple time scales; and, (3) development is the result of bi-directional coactions (i.e., interactions between the various subsystems within the organism, and between the organism and environment). In fact, these common themes are drawn from the systems science literature.

The key features of Gottlieb's (Gottleib, 1992, 1998; Gottlieb, et al., 2006) conceptualization of developmental systems include the coactions between organism and context (probabilistic epigenesis), a focus on the ecology (both social and physical) in which an organism develops, individual differences and a life-span perspective on development. The Thelen and Smith (2006) dynamic systems theory draws heavily from the systems science literature on complex and nonlinear systems and applies technical analyses to the study of infant motor coordination and speech production (see too Keller, 2005; Lerner, 2002). Holistic person-context interaction theory (Magnusson & Stattin, 2006) is grounded in interactionism, holism, interdisciplinarity, and the longitudinal study of the individual, which ultimately highlight the synthesis of the person-environment system. Wapner and Demick's (1998) developmental systems theory is holistic, developmental, and systems-oriented. The Ford and Lerner (1992) dynamic systems theory is a meta-theory of development that is relational by nature, multilevel and multivariate in organization, which accounts for the relative plasticity manifest across the life span by considering the individual as an open and self-regulating system that influences and is influenced by dynamic processes. These theories all draw from the literature in complexity, cybernetics, and dynamical systems, however; most mine this literature for its heuristic potential and fall short of adopting the analytic methodology.

Several key concepts that are relevant to systems science emerge from these theories; development is seen as occurring within a multi-level, holistic system in which all of the levels

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are potentially relevant. For example, in the study of gene-environment interactions, genes are not considered fixed entities that drive the developing system *en toto*. Rather, they are embedded within multiple levels of a system and it is the interplay of all of the components in the system that direct an individual's development (Gottleib, 1992, 1998). These theories reflect the notion that development does not occur at a single level of the system in isolation, but rather emerges as a result of the bi-directional interactions that occur between entities at the same level (e.g., cell-cell) and across levels (e.g., cell-tissue) (Fogel, 1999; Lerner, 2002; Magnusson, 1995; Wapner & Craig-Barry, 1992). Furthermore, temporal complexity is recognized as critically important to the concept of development. Developmental events occur at multiple time scales and vary across the system, e.g., synaptic transmission occurs within milliseconds, cell division happens in hours or days, while language acquisition takes place over years (Thelen & Smith, 2006).

These levels of organization are integrated and are not discrete; it is the dynamic bidirectional interactions between individual and context that produces development (Lerner, 2002, 2006; Magnusson, 1995; Magnusson & Stattin, 2006). According to the modern interactionist perspective, development is based on two types of interactions: Inner interactions refer to the bidirectional relationships occurring beneath the skin of a single individual; while outer interactions refer to the bidirectional relationships between a person and his or her environment (Magnusson & Stattin, 2006). Thus, the root of development can be found in the dynamic, bidirectional interactions between components in the system which include the individual and the surrounding context (Gottleib, 1992, 1998). New forms and processes emerge from self-organization of the system which involves an iterative process whereby each system state is shaped by previous states (Magnusson & Stattin, 2006; Thelen & Smith, 2006; van Geert, 2000).

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Plasticity refers to the soft assembly of the system and implies that there is potential for change across the life span and across multiple levels of scale. Relative plasticity recognizes that this capacity for change is not limitless, but rather, that it is constrained by both past development and contemporary ecological conditions (Ford & Lerner, 1992; Lerner, 1996, 2006). Plasticity is a key concept that pervades developmental systems theories. In order to study plasticity appropriately, the methodologies employed must be capable of coping with growth and change, not as extraneous variables to be factored out, but as phenomena worthy of study in their own right. Systems science methodologies fill this requirement.

Systems Science Concepts as they Relate to Developmental Science:

Dynamic Change Over the Life Course

Developmental science shares with systems science a central interest in change over time. The evolution of the state of complex systems give rise to complex, rich, and sometimes counter-intuitive dynamics; the trajectories followed by individuals over their life course are an exemplary illustration of many of these phenomena. For example, knowledge, coping strategies, and self regulation are developed and evolve over time. Turning points at various stages of the life course can profoundly affect the course of development. Crises may motivate personal or family transformation, or elicit in an individual with poor coping skills a reduced sense of self-efficacy and depression. The tools of complex systems modeling are well-suited to describe both those trajectories and the processes that give rise to them. Systems science methodologies provide multiple techniques for building models that specify the evolution of individuals in isolation and clustered as groups. Trajectories' qualitative behavior, stability and capacity to be influenced may change markedly over time – evolving, for example, from a situation which exhibits marked oscillations or sharp divergence (e.g., the escalation of conflict between two

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individuals, the rapid and self-reinforcing rise in an individual's sense of self-efficacy) to a situation of stasis, an "equilibrium" in which the various influences are in balance (e.g., stable relationships). Such models also help us understand why – for example – interventions that have relatively large impact in the short-term will sometimes yield little benefit in the long-term, and why interventions that attempt to nudge the trajectory (system behavior) in one direction may do so, but sometimes only after a period of time in which an apparent or true shift in the opposite direction has been observed. For example, a shift of emphasis from treatment to prevention may lead to an initial period where treatment resources are insufficient, only to eventually yield a situation where those same resources are more than adequate - once preventive measures have had time to reduce case volume below the threshold where resources can cover service demand (For example, see Milstein, Homer, & Hirsch, 2010).

Emergent Phenomena and Cross-Level Interactions

A notable feature of complex systems is the presence of distinct phenomena at different spatial and temporal scales. Some of these distinct patterns reflect structural regularities of the system, but others reflect emergence – the appearance of qualitatively distinct behavior and patterns at different scales and/or over time that arises as an unintended consequence of diverse interactions. Examples from developmental science can be found in how patterns in communities (e.g., clusters of dysfunction at the neighborhood level) influence but are distinctive from the patterns seen at the level of the individual. System science tools provide us both with a means of understanding such emergent phenomena at a particular level and with straightforward techniques for building models of these phenomena that directly incorporate cross-level interactions. For example, while a youth's capacity for self regulation may be an individual phenomenon, the expression of that capacity is affected not only by the behavior of other individuals, but also by factors at the family, school, and neighborhood levels (Urban, Lewin-Bizan, & Lerner, 2010). Conversely, school administration or neighborhood dynamics will be affected not only by trajectories of individuals but by emergent patterns arising from myriad inter-individual interactions as well as by behaviors at other levels of the system. System science tools allow for very flexible description of such diverse multi-level and multi-context interaction effects within simulation models.

Bidirectional Feedback

Feedback loops are cyclic causal structures within a system. A change in one factor in such a loop results in one or more changes in other factors, which in turn affect other factors and so on, eventually coming back to change the very factor where the cascade began. Thus, the effect of the original change is “fed back” to the originating factor, forming a “loop”. The ultimate effect is that the original change is either amplified (positive feedback) or counteracted (negative feedback) by the net effects of the feedback loop. While traditional methods of analyses are not capable of capturing this type of causality, systems science methods are expressly designed to include feedback loops as key drivers of the behavior of complex systems. Systems science methodologies not only provide techniques for describing and understanding the dynamic implications of such feedback, but also for helping to identify them in the first place and are useful for measuring their impact on the system.

Some general observations about feedback loops are worth noting. Positive (also called reinforcing, to avoid normative implications) feedback leads to instability and accelerating rates of change. Positive feedback can be thought of as having an amplifying effect in the system – whether or not those effects are subjectively experienced as good or bad. Feedback phenomena are surprisingly ubiquitous and the reader will recognize them as a familiar part of everyday experience. One familiar example of positive feedback is the howl of a microphone placed too near to a speaker, where a minute sound is repeatedly amplified, to the point where it overloads the capabilities of the speaker. The deleterious nature of many positive feedbacks has been recognized with the term vicious cycles. Familiar examples are arms races, cycles of addiction, erosion of trust in relationships, escalation of family discord, etc. Such cycles are also a marked feature of the life course. For example, exposure to a diabetic mileu *in utero* is suspected of triggering greater risk of growing overweight and diabetes in offspring, and contributing to a vicious intergenerational cycle of rising diabetes prevalence (Osgood, Dyck, & Grassmann, in press. Positive feedback can be beneficial, and in such situations are frequently termed "virtuous cycles." Compounding interest is a familiar example of a virtuous cycle – as interest is earned, it is combined with the original principal, thereby increasing the funds on which the interest is calculated, resulting in ever growing returns. Positive feedbacks are notable not just for their unstable character, but also for triggering divergence in trajectories over time. Because of positive feedback, two situations that are initially very similar may lead to strikingly different long-term outcomes. For example, organisms with the same genetic makeup (i.e., monozygotic twins) can develop markedly different phenotypes if reared apart (Gottleib, 1998).

Negative feedbacks are alternatively termed "balancing" or "regulatory" feedbacks, reflecting their "goal seeking" role in maintaining a system in equilibrium and resisting change. In contrast to positive feedback loops whose effects are amplifying or reinforcing, negative feedback loops are defined by their tendency to keep specific variables within a specified range, thus keeping the system in balance. Perhaps the most familiar examples of such feedbacks are those associated with maintaining some form of homeostasis. For example, dehydration can trigger a feeling of thirst, which causes us to reach for a drink of water, in an effort to keep the body's hydration level fairly constant. Similar cycles govern eating, sleep, human immune response to infection, response to exertion, etc. In developmental science, the concept of self regulation is an example of negative feedback.

Feedback loops are readily observed at a policy level. A policy decision to intervene is often made when parameters in the system go outside a desired range, creating a negative feedback loop. Such negative feedback loops are also frequently evident in the form of policy resistance, which refers to the tendencies for the benefits of many well-intentioned policies to be delayed, defeated, or diluted. Balancing loops, in an effort to keep the system in check, make it hard to effect change in the system because the interventions are met with a counteracting effect of the system to resist that change. For example, if childhood obesity rates go above a desired level, policies are enacted to bring obesity rates down; once rates are down, policies may fall by the wayside because the problem has abated. Thus, the feedback loop - obesity rates stimulate policy action which affects obesity rates which in turn cause further action (or inaction). The loop reflects the common observation that urgency to act is absent unless obesity rates climb into intolerable territory.

Methodological Challenges in Developmental Science and the Potential Use of Systems Science Methodologies

Philosophically systems science concepts have already been applied as is evidenced in the robustness of the developmental systems perspective; the addition of systems science methods to the developmental science toolbox has the potential to augment the ability to address developmental science research questions. Traditionally, approaches to studying development have taken a variable-oriented approach that tends to assess aspects of the system in isolation and thus present an incomplete and potentially inaccurate view of development (Lerner, 2002;

Magnusson & Stattin, 2006). A variable-oriented approach is primarily focused on applying statistical methods to the study of linear relations among variables and assumes uni-directional causality. Development is understood by summing the results of studies of single aspects of development (i.e., biological, behavioral, environmental, etc.). This empirical investigation of specific mechanisms and underlying processes is necessary; however, it can and should be complemented by a more holistic-interactionistic approach (Magnusson & Stattin, 2006). From a developmental systems perspective, the unit of analysis is the relational, organism-in-environment system and thus provides a person-oriented approach (Lerner, 2002; Magnusson & Stattin, 2006; Overton, 2010; Wapner, 1987, 1995; Wapner & Demick, 1998). Therefore, causality is not attributed to the individual, but rather, to the individual, the context in which the individual is embedded, and the interactions between the individual and the surrounding context (Fogel, 1999). Since the system itself is the focus of analysis, the research questions are no longer about beginning and end states, but rather on the *process* of development between states (Adolph & Robinson, 2008). Specifically, this perspective calls for a focus on the processes involved in the dynamic relations between individuals and their ecology (Lerner, Lerner, De Stefanis, & Apfel, 2001).

The current reliance on reductionist methods to study such dynamic relations is based in large part on the very real measurement and methodological challenges present in developmental science. It is important to note that we are not suggesting that systems science methodologies should or can supplant currently employed methods, but rather, that they should be used in conjunction with traditional empirical methods including longitudinal investigations, cross-sectional studies, and experimental paradigms. One of the primary criticisms of "new" methodological techniques is that they take on the characteristics of a fad and are implemented

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simply for their popular appeal (Sampson & Laub, 2005). This criticism is important and should be heeded when considering applications of systems science methodologies. We are not suggesting that these methods present a solution for all methodological problems ever encountered, nor do we mean to suggest that they be applied liberally without careful consideration of both underlying theory and the theory's fit with the model. Rather, we are suggesting that these methodological tools can be applied to specific sets of questions within the developmental literature and are particularly suited to questions that are derived from the developmental systems perspective.

Most research falls into three broad categories which will be discussed in detail later: 1) Theory generation and exploration (which includes proposing theoretical constructs, interactions amongst those constructs to be tested, and hypothesis generation); 2) Theory testing (which includes empirically testing competing hypotheses); and, 3) Policy analysis (which is the focus of a great deal of applied developmental science and includes the use of analytical methods to compare potential interventions designed to alter the system). Systems science methodologies' strongest potential contribution is in the first and third aforementioned areas: theory generation/exploration and policy analysis (including comparisons of several potential interventions). To date, the focus in developmental science has been on theory testing and the primary methodologies that have been employed in relation to the developmental systems perspective are longitudinal and cross-sectional designs (Collins, 2006; Wapner & Craig-Barry, 1992). More recent advances in the analysis of developmental trajectories have led to group-based methods of analysis (Nagin & Land, 1993; Nagin & Tremblay, 2005) and non-stationary time series modeling which accounts for reciprocal dynamic interactions (Molenaar, Sinclair, Rovine, Ram, & Corneal, 2009). Hollenstein, van Geert, Spencer, Lewis, and Fogel have also

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been leaders in applying systems science concepts and methods in developmental science. Most of their work has focused on applications of modeling techniques to cognitive developmental questions (and particularly those related to motor and perceptual development) (Schutte, Spencer, & Schoner, 2003; van der Maas, et al., 2006; van Geert, 1991).

Among the many contributions to date is the development of new empirical methods, such as state space grids that allow the mapping of behavior in real time, provide graphical representations of attractors, and measure developmental change based on differences in grid parameters (Hollenstein, 2007). These advances have focused on developing methods for theory testing. Despite these advances, there is much more that systems science methodologies can contribute to developmental science. Most notably, systems science methodologies have not been widely employed in the areas of theory generation and exploration, and policy analysis. In addition to continuing to develop novel systems-based methods for hypothesis testing, developmental science has the opportunity to apply already existing systems science methodologies to appropriate developmental questions.

Many system modeling methodologies are not new and indeed are now used routinely in fields such as corporate management, economics, engineering, physics, energy, ecology, biology, and others, precisely because these methods add value when combined with alternative techniques or unaided decision-making. By contrast, system-oriented methods have been slower to diffuse in behavioral and social science. Within the behavioral and social sciences, the public health field has pioneered efforts to address complex problems with systems science (Gerberding, 2005; Homer & Hirsch, 2006; Mabry, Marcus, Clark, Leischow, & Mendez, 2010; Mabry, Olster, Morgan, & Abrams, 2008; Madon, Hofman, Kupfer, & Glass, 2007; Milstein, 2008). For instance, systems science methodologies have already begun to be employed for

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planning and preparing against acute threats to public health (Lasker, 2004) such as global spread of a pandemic flu (Germann, Kadau, Longini, & Macken, 2006). These methodologies also show tremendous potential for use in developmental science. In particular, these methods can be used for theory generation/exploration and policy analysis as described below.

Theory Generation and Exploration

Systems science as a means of evidence synthesis. A primary value of systems science approaches is that they can be used to integrate work from a variety of disciplines in order to gain a better understanding of the big picture. Consider the complex array of factors known to influence the development of obesity in children: advertising can prompt consumption of unhealthy foods; lack of safe walking/bicycling routes contribute to low levels of physical activity, and greater time spent indoors watching television and playing video games; lower prices supported by agricultural subsidies foster consumption of calorie-rich food; genetic predisposition to obesity can contribute to excessive weight gain; social norms that favor excessive weight can contribute to acceptance of excess weight; and there is new evidence that sleep disturbance may contribute to obesity.

While this list of factors contributing to childhood obesity is incomplete, it illustrates the many disciplines that contribute to this conceptualization of obesity: psychology, physiology, genetics, advertising, urban planning, policy, and economics are all represented. Despite this wealth of evidence, and to some degree because of it, the answer to the question, "What causes childhood obesity and how can we reduce obesity prevalence in the near and long term?" is not straightforward. Systems science methodologies enable evidence drawn from many disciplines to be considered simultaneously in building a model of the system of childhood obesity. This model can then aid in determining the nature and strength of each of the component pieces

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individually and together with regard to the outcome of interest (childhood obesity). Thus, the modeling can serve to synthesize the literature and yield new insights.

Systems science models as heuristic tools. Systems science methodologies offer particular value as heuristic tools, helping simply to gain a better understanding of a phenomenon. This better understanding can, of course, lead to novel hypotheses to be tested using traditional methods. For example, an agent-based model could be constructed in which each "agent" was imbued with specific characteristics and assigned decision rules that would play out at each time step (e.g., one day) of the model. At initialization, agents might reflect population characteristics from an identified data set. If we were trying to understand childhood obesity, we might use data from the 1970s, prior to the obesity epidemic. Each agent would be assigned a particular gender and body weight consistent with this data. At each time step, each agent might have a certain probability of ingesting a small number of calories per day in excess of that required to maintain his or her weight. In addition, each agent might be programmed to mimic any overconsumption behavior if observed in his or her nearest neighbor at the next 10 time steps (i.e., if already over consuming, they might over consume by some additional amount if excess consumption was observed in neighbors in a given proximity). After some number of time steps, new weights for the population could be established, based on a totaling of the excess calories per day consumed over the entire period. Thus, it might be discovered that even if only a few people initially over consumed and only by a small margin, the contagion behavior might move rapidly through the population and reach nearly all members of the population and ultimately might result in substantial weight gain in the population over time, mimicking the pattern of weight gain observed in the obesity epidemic. If this result happened, it would be possible to state that this hypothesized mechanism (small margin of overeating mimicked by

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others) could be one plausible contributor to the observed population phenomenon. This observation could give rise to a new hypothesis that could be tested using traditional methodologies.

Models as a tool for hypothesis development. Modeling and simulation can greatly assist hypothesis generation and refinement. Often by examining a model's structure and responses to disturbance, a new insight is revealed that can lead to a new hypothesis. Hypothesis generation can be bottom up or top down. That is, a system characteristic or property may only "emerge" once the full model is put into place – a bottom up revelation. Alternatively, a hypothesis may be developed prior to the building of the model and the internal consistency of that hypothesis and its consistency with empirical data can be examined via simulation. In many cases, such model interaction can aid in undercutting or refining the hypothesis. More broadly, models can be thought of as ways to express, share, and refine causal hypotheses. Conceptual maps of the system reflect previously conceived hypotheses about how the system works. Mathematical or computational models are "calibrated" in order to quantify relationships according to the available evidence and provide some fidelity to the real world phenomena on which they are based. Model calibration is achieved by adjusting model parameters so that outputs match some available data. Of course, to avoid simply validating the model to the values at which it has been set, care must be taken to validate on a different set of data than it was calibrated on. Sometimes this validation is achieved by splitting the existing data set into pieces and using one half for calibration and then seeing if the model output matches the other half – a process called cross-calibration. See Osgood, et al. (this volume) and Orr and Evans (this volume) for examples of model calibration and estimation.

Policy Analysis

Systems science models for evaluating policy and informing decisions. Modeling approaches can also prove extremely valuable when one seeks to evaluate policies and determine trade-offs between alternative courses of action. Through simulations of various sample scenarios, much can be learned. For example, various "what if" scenarios are assumed given a set of initial conditions and model outputs are simulated over time. Each scenario could reflect a different set of policy actions. The model would be used to generate a series of outputs over time under each scenario (each of these being referred to as a simulation). Model outputs are then compared across simulations. Often the various intervention scenarios are compared to a "status quo" scenario in which no policy changes are implemented after the starting point. This "baseline scenario" allows one to observe any inertia inherent in the system, such as population growth or aging, and to anticipate what the extent of the problem would be in the absence of any intervention.

It is important to realize that model simulations should not be relied on as accurate predictions of what will happen – whether under the baseline scenario or any other scenario. Indeed, there are generally too many uncertainties regarding evolution of exogenous factors to provide a prediction of outcomes. Rather, simulations help us understand the underlying dynamics of the system, and characterize a range of likely outcomes, with each such outcome being conditional on a particular context. While specific future values cannot generally be known for certain, it is safer to look to the model for insight into likely future *trends* in the outcomes of interest.

Scenarios and forecasting. By simulating various policy scenarios and comparing the results, it becomes evident where the "leverage" points are in the system. That is, there may be policies that, even if put into full effect, have relatively little impact on the outcome of interest in the desired time frame, while other policies can have much greater impact, even with minimal effort. For example, implementing a policy that affects everyone in the population, such as universal pre-kindergarten (pre-k) which provides pre-k classes for all age-eligible children, would have a greater impact on increasing early literacy than intensive reading interventions for remediating select grade-school children. In the first instance, the entire population benefits while, in the second, only a subset of the population benefits.

It is also important to realize that model simulations simply provide information about what is likely under certain assumptions. They do not dictate what policy should be. For example, the results of simulations would not indicate that universal pre-k is the best policy and that offering reading interventions to grade-school children is not effective. Rather, the simulations simply might suggest reasonable hypotheses for how much and how soon each policy strategy will contribute. It may be prudent to offer reading interventions to grade-school children, but it would be unwise to expect this action to be the sole answer to reducing population prevalence of illiteracy or poor reading skills. Often a combination of policy strategies works best due to inter-policy synergies; by doing virtual experiments in which different policies are combined in different scenarios and simulated, the most potent combinations can be discovered.

Specific Systems Science Methodologies

Specific systems science methodologies include, but are not limited to: system dynamics modeling (Sterman, 2000), agent based modeling (Epstein, 2006), discrete event simulation (Banks, Carson, Nelson, & Nicol, 2010), network analysis (Wasserman & Faust, 1994), dynamic microsimulation modeling (e.g., Mitton, Sutherland, & Weeks, 2000), and Markov modeling

(Sonnenberg & Beck, 1993). These techniques (among others) are particularly well-suited for understanding connections between a system's structure and its behavior over time; anticipating a range of plausible futures based on explicit scenarios for action or inaction in certain areas; identifying unintended or counter-intuitive consequences of interventions; evaluating both the short- and long-term effects of intervening in the system; and guiding investments in new research or data collection to address critical information needs. Such tools have proven heuristic power, typically integrating data from various disciplines to gain an understanding of the "big picture" (Meadows, 2008).

Overview of Highlighted Systems Science Methodologies

This special issue highlights three systems science methodologies: system dynamics (Osgood, et al., this volume), agent-based modeling (Orr & Evans, this volume), and network analysis (Okamoto, et al., this volume). Each methodology is featured in one of the subsequent articles in this issue.

System dynamics. "System Dynamics" (SD) as a proper noun refers to a specific form of computational modeling that was developed in the 1950s by Jay Forrester at the Massachusetts Institute of Technology, by drawing on ideas in cybernetics and feedback control systems (Forrester, 1958, 1961). Keeping in mind that every model is a simplification of reality, SD is characterized by modeling a system as a set of interrelated compartments ("stocks" or "accumulations"), and by rates of transition between stocks or flows. Each such flow is typically associated with a specific mechanism by which individuals evolve over time. In a simple example, a model of a population could be divided into two compartments, males and females. The "stocks" (number of males and number of females) would rise and fall in each compartment according to births (or migration) and deaths. The "flows" associated with a stock (e.g., the births and deaths) collectively determine the rate of change of the stock over time (in calculus terms, its derivative). The current level of any stock then is the sum of the level of that stock at the previous time step plus inflows and minus outflows occurring during the intervening time interval. Feedback loops are quite often employed in SD modeling (e.g., population growth results in more people capable of reproducing , leading to an increase in births, leading to a larger population with even more births, etc.). The behavior of the simulated system over time emerges from the interaction of stocks and flows and is often driven in fundamental ways by the feedbacks that are present.

In accordance with Einstein's dictum to [m]ake things as simple as possible, but not simpler, a guiding principle in building SD models is that each compartment is only as granular as it needs to be. For example, if, for the problem being modeled, males and females will suffice, there will be just two compartments. But if, for example, age is also considered important, the sex compartments can be further disaggregated into different ages. Compartment stocks could be divided according to two or more age categories. If warranted, these compartments could be further subdivided according to ethnicity, socioeconomic status, or any other characteristics seen as necessary to address the research question. If deemed necessary, the compartments could even be broken down to the point that each one represented stocks associated with an individual person. In fact, it is worthwhile to note that some SD models do represent a single individual as the entire system with the compartments making up the important dynamic factors within that person; similar approaches can be extended to multiple people. However, because entities in an SD model are aggregated into compartments which are treated as homogeneous, SD is considered an *aggregate* or compartmental technique. Such models are capable of capturing non-linear dynamics, time-delayed effects, feedback phenomena, and

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(through disaggregation) heterogeneity. Because calculus forms the underlying mathematical framework for SD models, such models can be precisely (and often relatively concisely) specified. While full symbolic solution of such models is typically not possible, the models do also admit to a variety of types of formal mathematical analysis, which can yield insight into factors such as outcomes of long-term system evolution, possible types of behavior to be expected, and local system stability in response to disturbance. Among other uses, SD models are frequently used for evaluating the trade offs and consequences of various policy interventions, especially where resources are limited. In this context, they can uncover "worse before better" effects and other dynamic effects over time. An excellent non-technical introduction to the concepts of system dynamics modeling is *Thinking in Systems* (Meadows, 2008); a comprehensive text on system dynamics modeling is *Business Dynamics* (Sterman, 2000). Osgood, et al. (this volume) present a system dynamics model that explores the relationship between early life exposure to Tuberculosis infection on later life outcomes.

Agent based modeling. Agent based modeling (ABM), is also referred to as Agent Based Computational Demography (ABCD) and Agent-Based Computational Economics (ABCE). ABM has its origins in the 1950s with efforts in computer science and psychology to simulate intelligence and, more currently, distributed artificial intelligence (see Gilbert & Troitzsch, 2005). In contrast to SD models, which consider the system as a whole and then break it into as many parts as is deemed appropriate for the research question, Agent-Based Models are constructed from the bottom up. Individual "agents" are constructed using a software application (there are many) in which the modeler specifies the rules of behavior for each agent with associated probabilities. Agents are autonomous, interdependent, follow simple rules, and can adapt over time. Agents have the ability to interact with each other and can be situated in such a

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way as to replicate observed network connections, and/or modeled on a replica of geographic space. For example, ABM has been used to understand how individual residential preferences could lead to, in aggregate, segregated neighborhoods (Bruch & Mare, 2006). Other applications that may be of interest to developmental scientists are the use of ABM to understand how individual choice factors into marriage markets (Todd, Billari, & Simao, 2005), and to generate hypotheses about the potential impact of child maltreatment prevention interventions (Hu & Puddy, 2010).

With ABM, a modeler seeks only to capture the essential elements of agent behavior in the model; with such a model, the high-level behavior arises as emergent properties from the simulation and can give a sense as to how subsequent events could unfold. Because the models are based on explicit probabilistic rules associated with each agent, the models are stochastic rather than deterministic that is, there are theoretically many possible outcomes from a given starting point in a simulation. Therefore, numerous iterations of simulations are run in order to determine the likelihood of various outcomes.

Agent-based models are particularly well suited to endeavors where there are numerous heterogeneous characteristics of the agents and these characteristics are central to the problem under study. ABMs are extremely useful for examining potential outcomes of social experiments *in silico* without conducting any harm to human participants, or consuming extensive resources that might be required in the real world. They are also useful for studying adaptation and learning, and for examining interactions between agents and their effects. A good introduction to ABM can be found in *Growing Artificial Societies: Social Science from the Bottom Up* (Epstein & Axtell, 1996). Orr and Evans (this volume) apply agent-based modeling to

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a developmental question by exploring the long term diffusion dynamics in adolescent sexual initiation.

Network analysis. Network analysis is a general term for the study of the structure of relations between entities, be they flights between airports, electrochemical signaling among neurons, or connections between computer networks on the Internet. In behavioral and social science research, including developmental science, we are often concerned with *social* networks – the web of social ties within which people are embedded. Network analysis has its roots in numerous disciplines and modern Social Network Analysis (SNA) dates to the 1930s.

Social networks can be represented by a set of nodes and the ties that connect them. Each node corresponds to a "social actor", i.e., a person, organization, or other entity. The "ties" are the social relationships between them - often social resources such as information, emotional support, or material aid that is exchanged between social actors. Social network analysis consists of a set of tools or methods that can be used to analyze the structure of networks, examine how this structure evolves over time (e.g., Snijders, Steglich, & van de Bunt, 2010), and draw inferences about whether structural characteristics (e.g, connectedness, average distance between nodes, clustering) are related to some outcome of interest (see Wasserman & Faust, 1994).

To illustrate, consider that while we know that children and adolescents are socialized by their friends, much less is known about the timing, nature, and conditions surrounding peer-to-peer influence. Work of Espelage and colleagues (Espelage, Holt, & Henkel, 2003; Holt & Espelage, 2007) has demonstrated that social network analysis can illuminate peer influences on bullying. Social network analysis has also been used to understand the spread of obesity through adolescent peer groups (de la Haye, Robins, Mohr, & Wilson, 2010), to compare how social networks change following breast cancer diagnosis among women of different ages (Ashida,

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Palmquist, Basen-Engquist, Singletary, & Koehly, 2009), and to devise peer network interventions to counteract the spread of smoking (Valente, Unger, Ritt-Olson, Cen, & Anderson Johnson, 2006)[1]. A concise overview of social network analysis can be found in Borgatti, et al. (2009) and *Social Networks and Health* (Valente, 2010) is an excellent text. Okamoto et al. (this volume) apply network analysis to a developmental question by examining the relationship between social network status and depression among adolescents.

Systems Science Methodologies Applied to Developmental Science Questions: An Example

We sketch here an example of a developmental science question that has significant policy implications and has received considerable media attention. In this example, we explore how the topic of adolescent exposure to “sexy media” (sexually explicit content in the mass media) and its influence on sexual behavior has traditionally been studied in the developmental literature. We then discuss how this topic could be conceptualized as a developmental system that is amenable to a system dynamics modeling approach.

Several recent studies on the relationship between adolescent consumption of “sexy media” and sexual behavior have received attention in the popular press (Brown, et al., 2006; Chandra, et al., 2008; Collins, et al., 2004). Brown, et al. (2006) and Collins, et al. (2004) tested and found that consumption of “sexy media” by adolescents predicted adolescent sexual initiation, while Chandra, et al. (2008) found that exposure to sexual content on television predicted teen pregnancy. Each of these studies concluded that limiting adolescents’ exposure to sexy media could reduce adolescent sexual behavior. These studies all utilized traditional statistical methodologies (i.e., regression analyses) to essentially test whether a sexy media diet predicts adolescent initiation of sex: Sexy Media Diet→ Initiation of Sex.

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More recently, Steinberg and Monahan (2010) have argued that the results of these previous studies are actually due to selection effects and that there is no clear causal relationship between a sexy media diet and adolescent initiation of sex. To control for these selection effects, propensity score matching was used to reanalyze the data collected by Brown et al. (2006). When preexisting differences between adolescents were controlled, no direct relationship between a sexy media diet and adolescent initiation of sex was found. To help explain these findings, Steinberg hypothesized a mediation model whereby openness to sex leads to adolescents having a greater propensity for viewing sexy media, which in turn affects adolescent sexual initiation (Steinberg, 2010): Openness to Sex→ Sexy Media Diet → Initiation of Sex.

Steinberg and Monahan's (2010) use of propensity score matching to reanalyze the data collected by Brown et al. (2006) is a significant methodological advance that leads to vastly different conclusions based on the same data. In theory, both researchers are proposing a model that could be conceptualized as a developmental system with interactions between an individual and his/her environment. However, the models that they tested do not account for the dynamic nature of human development. Steinberg's model proposes that openness to sex precedes seeking out a sexy media diet. However, it is entirely possible that the relationship between these variables operates in the opposite direction such that by consuming sexy media, adolescents are more open to sex. Thus, the question arises, does openness to sex lead youth to seek out a sexy media diet, or is it the other way around, does consuming sexy media lead youth to be more open to sex? Or, could both be true? Ultimately we would like to know, how does the relationship between openness to sex and sexy media consumption relate to adolescents' behavior - initiation of sex? A dynamic model of development that can capture the feedback mechanisms between individual agency (openness to sex and initiation of sex) and context (sexy media diet) is needed to capture this complexity. A system dynamics modeling approach that explores these dynamic relationships can help to further understand the phenomena and aid in refining the hypotheses that can subsequently be tested using traditional statistical techniques. Although media effects are not explored, Orr and Evans (this volume) examine a similar topic (diffusion dynamics in adolescent sexual initiation) using another systems science method, agent-based modeling.

Figure 1 presents the scenario in an individual-level system structure diagram, which focuses on factors leading up to but not beyond the initiation of sex. System structure diagrams differ from the stylized stock and flow diagram depicted in Figure 1 of Osgood et al. 2010 (this volume) in their representation not only of stocks and flows, but of also other variables and associated feedback loops. As already noted, within system dynamics, stocks are accumulations of some quantities or components that collectively specify the state of the system at a given instant in time. In this example, openness to sex and the likelihood of initiation of sex are the stocks. Each of these stocks have accompanying flows (indicated by a double lined arrow) leading into the stock. Such flows capture the influence of processes that increase or reduce each of these stocks over time. The valves on the flows indicate the rate of flow. In this example, consumption of a sexy media diet can influence the rate of flow into the "openness to sex" stock. More consumption of sexy media may increase adolescents' openness to sex which in turn leads to more consumption of sexy media, and so on. Similarly, consumption of a sexy media diet can influence the rate of flow into the "likelihood of having initiated sex" stock– an example of a reinforcing feedback loop (labeled "Sexualization" in the diagram). Greater consumption of sexy media may increase adolescents' likelihood of initiating sex. The stock and flow diagram also takes into account that an adolescent's openness to sex increases the likelihood of initiating

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sex. The diagram also accounts for other covariates and their influence on both the rate of increase in openness to sex and the increase in likelihood of initiation of sex. For simplicity, the covariates are not listed individually but may include such variables as gender, SES, parental education, parents' views on sex, etc.

<<Insert Figure 1 here>>

At this point, the model presented here is purely conceptual and not tethered to any real data. We present this conceptual model as an example of how a systems science method could potentially be utilized. We refer the reader to the subsequent papers in this special issue for a more in depth exploration of the applications of systems science methodologies. The process of explicitly formulating and sharing such a model could offer value in hypothesis generation. The next step in building a system dynamics model would be to specify the hypothesized relationships relating different variables in the model. This process could draw on understanding from published studies of intervention trials and reports from the secondary literature. In order to use the model for hypothesis testing or policy analysis, we would need to build a model that could be simulated. To build such a model, the modeler would need to specify values for model parameters. Values for some model parameters might be directly estimated from longitudinal data. To complement or supplement available data, a modeler may also seek the counsel of domain experts, who could advise as to the dynamic patterns to be expected, or the ranges of plausible parameter values that might be obtained. Other model parameters might instead be estimated via calibration, a parameter estimation process in which one or more parameters are adjusted so as to allow the model predictions for a given situation to best match a set of available longitudinal data for that situation, such as follow-up data involving repeated measurements of openness to sex and media diet composition. While such model estimation techniques can be

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sophisticated (taking into account measurement error and model error), their mastery can also involve surmounting a significant learning curve.

In order to be simulated, a model such as this would further require specification of some initial state. This state represents a snapshot of the situation at the start of the simulation period. The representation of this state could be informed by drawing on the original data collected by Brown et al. (2004) as well as by other studies that examined similar variables and processes. Rather than replacing earlier contributions, the process of creating the envisioned model would build on top of and incorporate the findings from such studies. The simulation framework would thus accompany and leverage analyses undertaken with other analytic tools, such as path analysis, hierarchical linear modeling, and more traditional statistical methods.

Much of the exploration with the model would proceed in a scenario-driven manner. Such exploration allows for investigating "what if" questions using the model. Some of these questions might be articulated to study the consistency of hypotheses captured in the model with empirical data. For example, the model parameters might be set so as to characterize certain contexts that have been studied empirically. Simulations could then be conducted to identify the consistency of its dynamics with patterns observed in longitudinal datasets.

Reflecting the fact that the hypotheses of concern have significant policy relevance, such a model could also be used for policy study. Specifically, once confidence has been established in the robustness of a given model, the model could be run in various scenarios to explore the possible implications of policies. For example, what would happen if media literacy education was provided to parents? Following the definition of the baseline scenario, the modeler could then run alternative scenarios that vary particular factors to investigate the system-wide consequences of various interventions, or the impact of changed assumptions. The model could further be used for scenario-based sensitivity analysis by systematically investigating the degree of impact that particular uncertainties have on model outcomes over time. Quantities for which the current range of uncertainty yields pronounced differences in model outputs could then serve as priority targets for further investigation.

Conclusions

At its core, developmental science seeks to explore bi-directional relationships, interactions across contexts and organizational levels, and dynamic change over time. As a field, developmental science must work to identify and utilize pioneering approaches to the study of developmental topics that have ramifications for how we understand and alter developmental outcomes. Despite major statistical and methodological advances, the field is in need of methodological tools that integrate existing and new research, at different levels of analysis, account for bi-directional feedback processes and address the complexity inherent in change that occurs throughout the life span. Systems science methodologies (including system dynamics, agent based modeling, network analysis, etc.) are well suited to such endeavors, but have yet to be harnessed to their full potential by developmental scientists.

The application of systems science methods to developmental science questions holds tremendous promise. There are many areas of developmental science where systems science methodologies may be particularly appropriate. Systems science methodologies can help us to explore and understand (while not implying hypothesis testing necessarily): the relative effectiveness of early childhood interventions on cognitive, social, and health outcomes in later life; how variable family, school, and neighborhood resources affect adolescent development; why ethnic disparities continue to persist in educational achievement; and the role of psychosocial stress in health disparities, to name a few. These and many other developmental science topics are ideally suited for exploration with systems science methods.

Systems science approaches integrate multiple levels of analysis – from cells to behavior to society – to understand the ways in which individual, contextual, and organizational factors interact over time. One of the primary advantages of utilizing systems science methods as a complementary method is that nonlinear relationships, the unintended effects of intervening in the system, and time-delayed effects are often missed with traditional reductionist approaches, whereas systems methods excel at detecting these effects. Because of its unique ability to consider simultaneously both the whole system and its individual parts, the application of systems science methodologies in developmental science shows promise for unlocking the secrets of complex, multidimensional issues and for transforming this knowledge into effective interventions that can fundamentally change developmental outcomes.

In sum, this article serves as a "call to action" for the developmental science community to begin to educate itself in the use of systems science methodologies and to apply them in its research endeavors. Specific actions that developmental scientists can take include: 1) educating themselves in systems science methodologies through readings (including those cited in this article) and other educational resources (OBSSR at NIH provides such resources http://obssr.od.nih.gov/scientific_areas/methodology/systems_science/index.aspx); 2) identifying systems scientists who may be interested in applying their methodological skills to developmental science problems and approaching them about collaborating; this outreach can be done by attending systems science oriented conferences (e.g., the Social Computing, Behavioral-Cultural Modeling and Prediction conference makes a deliberate attempt to network attendees

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across disciplines. See http://sbp.asu.edu/index.html); 3) once sufficient knowledge and expertise is acquired, pursue research projects utilizing systems science methodologies[2].

The remaining three articles in this special issue provide concrete examples of systems science methodologies applied to developmental science questions. These articles mark an initial foray into the application of systems science methods in the field of developmental science. There are many as yet unexplored applications of these methods. We hope that this special issue will resonate with developmental scientists and that future studies will explore new and innovative ways in which systems science and developmental science can be integrated.

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Footnote

[1] The Add Health database (http://www.cpc.unc.edu/projects/addhealth) is a rich source of publicly available, longitudinal, network data relevant to the interests of developmental scientists.

[2] These opportunities are disseminated via the BSSR-Systems Science Listserv. Contact the list owner (Patricia Mabry: mabryp@od.nih.gov) to join the listserv

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