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Complex Systems Research in Educational Psychology: Aligning Theory and Method

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Abstract

The purpose of this work is to provide an overview of complex systems research for educational psychologists. We outline a philosophically and theoretically sourced definition of complex systems research organized around complex, dynamic, and emergent ontological characteristics that is useful and appropriate for educational psychology. A complex systems approach is positioned as a means to align underexplored elements of existing theory with appropriate interaction dominant theoretical models, research methods, and equation-based analytic techniques. We conclude with a brief discussion of several foundational topics for complex systems research in educational psychology.

There is a gap between educational psychology theories of motivation, cognition, and engagement and the common research methods used to test and refine them. Theories in educational psychology describe complex, dynamic, and emergent processes that shape intra- (e.g., cognition, motivation and emotion) and inter- (e.g., teacher–student, student–student, parent–child interactions, collaborative teams) person phenomena at multiple levels. These processes are fundamental characteristics of complex systems (CS). However, theory in educational psychology that implicitly or explicitly treats phenomena of interest to educational psychologists as complex is rarely examined using CS methodology, or tends to translate CS to linear cause–effect models that do not adequately describe the theory. CS approaches to research can be used to improve the alignment between theory and research method in educational psychology.

Although dominant theories in educational psychology reflect many CS perspectives, they are not typically explicitly framed, developed, or empirically investigated within a CS framework. It is only recently that educational psychology scholars have begun to align theory and method so that the basic theoretical underpinnings are accompanied by methodology that acknowledges the assumptions of CS (Koopmans & Stamovlasis, 2016). We contend that empirical CS research designs should flow naturally from theories in educational psychology through alignment with appropriate methodology and method. Accordingly, the purpose of this article is to provide guidance for translating theoretical complexity into CS research designs and methods. Our intent is not to provide a

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comprehensive review of the history and principles of CS science or complexity thinking (see Davis & Sumara, 2006; Mitchell, 2009; Patton & McMahon, 2014; for these types of reviews). Rather, we define the salient, domain general characteristics of CS, providing an ontology that can be used to guide CS research methodology and analyses in educational psychology.

We begin our discussion of how to bridge the gap between theory and method from an ontological perspective. Research is often driven by the development of conceptual models that reflect ontological assumptions about the characteristics of the external world. Ontological assumptions are a set of defining characteristics that describe the assumed form and nature of a given phenomena. Ontological assumptions are represented by the properties and relations used to describe reality within a domain of study (Guba & Lincoln, 1994). We bring together the terms and concepts of CS science and complexity thinking to define the differences between component dominant and interaction dominant models, making the argument that interaction dominant models can provide useful representations of CS in educational psychology. Calling upon existing frameworks and philosophy in the field (Bunge, 2000; Jacobson, Kapur, & Reimann, 2016; Kaplan, Katz, & Flum, 2012), we establish an ontological framework that defines the *complex* macrobehavior of systems, the *dynamic* microinteractions of system components, and the *emergent* mechanisms that produce system outcomes (Mitchell, 2009; Sawyer, 2004; Wan, 2011). These three ontological characteristics form the foundation of a CS approach to investigating interaction dominant models in educational psychology (e.g., motivation, engagement, cognition, and learning) that may be leveraged to close the gap between theory and method. After this, we describe some empirical methods suitable for executing CS research. We summarize several equation-based data intensive techniques for CS research that have not gained traction in the field: nonlinear time series analysis, network analysis, and dynamic modeling. We demonstrate conceptually how these methods and analytic techniques can be executed using our ontological framework as a guide.

DEFINING CS FOR EDUCATIONAL PSYCHOLOGY

A CS is a collection of interacting components (i.e., those that interfere, cooperate, or collaborate) that gives rise to complex behavior (Mitchell, 2009; Strogatz, 1994). System components can take material, conceptual, or semiotic forms such as individual students, teachers, and technological objects; motivation, behavioral, affective, epistemological, and cognitive variables; or words, text, symbols, and discourses (Bunge, 2000). Components within CS interact over time to produce emergent outcomes at higher levels of analysis that are characterized by nonlinear behavior such as sudden transitions from one state to another or bifurcations in topological structure. Emergent outcomes are more than the sum of their parts, meaning the complex behavior cannot be reduced to the components that make up the system (Holland, 2006). For example, imagine that a student suddenly becomes motivated to learn during a lesson. A complex collection of shifting factors, too many to describe or perfectly model (e.g., prior knowledge, self-perceptions and beliefs, content, context, etc.) are related to the student's energy to engage with the learning task. The motivation emerges from the experience itself and cannot be reduced to or exactly explained by a small set of isolated factors (Nakamura & Csikszentmihalyi, 2002).

Because CS contain multitudinous interacting, changing parts they are often described as *interaction dominant* (Richardson, Dale, & Marsh, 2014). This means that the collection of system components producing the outcome is softly assembled: The role of components in producing the outcome and the strength of the relationships between them shift and change over time. As a result, the collection of variables that produce the outcome cannot be reduced to a perfectly, empirically defined set that, in total, accounts for the outcome. In contrast, a *component dominant* system is rigidly assembled and can be precisely defined by its components so that outcomes can be nearly perfectly reduced to the sum of their parts (Holden, Van Orden, & Turvey, 2009). Because CS are interaction dominant, they are often depicted as a complex network of components with an outcome proposed to emerge from their complex interactions. In contrast, component dominant systems have a defined causal structure, with an outcome that is proposed to be determined by the relationships among the components. See Figure 1 for a graphical representation of a generic interaction dominant system and a visual comparison between interaction dominant and component dominant models.

Interaction dominant systems and component dominant systems each have different mechanisms and sets of underlying assumptions that govern their behavior. In component dominant systems the relationship among the components is considered linear, meaning that the role of the components in the model and the strength and direction of their relationships are considered stable across time and context, or nomothetic (Cronbach & Meehl, 1955; Hempel, 1965). Feedback loops describe system maintenance, where independent variables influence dependent variables in a cyclical fashion. Component dominant models are typically examined using linear statistical methods (Fisher, 1925), which assume an underlying normal distribution, independent observations, and homogeneity of variance. Any disconnect among the system components is attributed to random measurement error or weak, idiosyncratic, independently acting factors. Kaplan and colleagues (2012) described model characteristics like these as central to a linear, deterministic way of viewing research and the dominant paradigm in educational psychology.

In interaction dominant systems, the relationship among the system components is considered interdependent and nonlinear, meaning that variable roles and the strength and direction of their relationships change over time and context to context and are dependent upon other system components. Supervenience describes system maintenance, where emergent states influence the equilibrium of interactions among system components (Sawyer, 2004; Witherington, 2015). Quantitatively, interaction dominant models are typically examined using intensive data (i.e., time series and network data), which assume an underlying power law distribution, dependent observations, and heterogeneity of variance. Because all system components are dependent upon one another, the dynamic behavior of a critical indicator over time can contain information about the entire system (Takens, 1981). Davis and Sumara (2006) used the phrase complexity thinking to define the dominant paradigm in CS research.

The distinction between interaction and component dominant models has implication for theory development and empirical research. Theory building and testing are often accomplished through the development of two forms of related submodels: (a) the conceptual or theoretical model and (b) the statistical model (Sloane & Wilkins, 2017). Established through a series of design choices, these models stand between theory and the phenomena under study and are central to the transportability or generalizability of findings (Chronbach & Shapiro, 1982; Lincoln, Guba, & Pilotta, 1985). These two models are considered a simplification or approximation of more complex conceptual or social systems (Sloane & Gorard, 2003). The two submodels need to overlap conceptually, and be commensurate with existing theory, to produce a working or useful research model (Sloane & Wilkins, 2017). Although theoretical postulations in educational psychology often describe interaction dominant phenomena, they are regularly reduced to complicated theoretical models with component dominant characteristics that lend themselves to linear empirical testing. And ergodicity, or the assumption that the structure and strength of the relationships among model components are stable overtime, is often assumed and rarely tested (Koopmans, 2015). In a review of motivation theory, Kaplan and colleagues (2012) described many theoretical models as being complicated to the point that they are often untenable to test using linear methods; thus, statistical models are used to further reduce theoretical models to subsets of component dominant models to test linear, nomothetic hypotheses. However, when complex theory is reduced to linear models, a gap between theory and model is produced that restricts understanding and theory refinement. Even if researchers adopt a flexible epistemological stance that positions the state of knowledge as evolving and changing(i.e., over time and context to context) they may still utilize linear, cause–effect models to describe the external processes underlying phenomena of interest. An ontological shift in thinking about complex phenomena may help researchers to develop interaction dominant models as a basis for their research that more accurately describe complex, dynamic, and emergent processes.

CS AND THEORY IN EDUCATIONAL PSYCHOLOGY

CS research approaches can rise among existing theory in educational psychology that focuses on dynamic and complex combinations of factors that shape and promote learning. Some theoretical perspectives focus more heavily on intraperson processes that may be shaped by interactions with context, whereas other perspectives focus more heavily on interperson processes and place interactions between individuals at the center of inquiry. In one intra-person example, Kaplan and Garner (2017) described a Dynamic Systems Model of Role Identity that considers ontological and epistemological beliefs, purpose and goals, self-perceptions and self-definitions, and perceived action possibilities as mutually regulating elements within a contextually embedded system. In the model, system components are described as interdependent, and identity development is viewed as an emergent, nonlinear process that involves restructuring of the strength and relationships among role identities over time and across context. Identity development is theorized to be shaped by intra-and interperson processes that are mediated by sociocognitive and cultural forces. Interest in mutually regulating, emergent processes is shared by others who don't always explicitly operate from a CS point of view but situate intraperson processes at the center of their theories such as motivation science researchers interested in how affect and motivation energize action (Bandura, 1977; Deci & Ryan, 2002; Ford, 1992; Husman, Hilpert, & Brem, 2016; Linnenbrink-Garcia, Rogat, & Koskey, 2011; Op't Eynde & Turner, 2006; Pekrun & Perry, 2014; Pintrich, 2003; Renninger & Hidi, 2016; Sheldon, Cheng, & Hilpert, 2011). It is also shared by researchers in epistemology seeking to understand how people adhere to particular norms and practices related to shared beliefs about knowledge and procedures (Greene, Sandoval, & Bråten, 2016).

In another example, Scardamalia and Bereiter (2006) offered an interperson theory of knowledge-building communities. Calling heavily upon CS theory to explain their framework, they argue that learning is a self-organizing process that exists at both individual and collective levels of advancement. They call upon Popper's (1973) concept of world three, where knowledge has an external object-like existence that emerges from collaborative behaviors. These arguments are similar to engagement researchers who may not explicitly call upon CS but situate social processes involving interperson interactions and collective action at the center of their theories (Connell & Welborn, 1991; Connor et al., 2014; Finn & Zimmer, 2012; Järvenoja, Järvelä, & Malmberg, 2015; Lawson & Lawson, 2013; Marchand & Skinner, 2007; Shernoff et al., 2016; Skinner, 2016; Skinner, Furrer, Marchand, & Kindermann, 2008). They are also shared by collaboration researchers interested in joint meaning making in both face-to-face (Dillenbourg, 1999) and computer-supported (Stahl, Koschmann, & Suthers, 2006) environments, as well as distributed or team cognition (Cooke, 2015).

In an attempt to integrate CS principles into educational psychology research, Jacobson et al. (2016) recently offered the Complex Systems Conceptual Framework of Learning. Calling upon decades of CS science that distinguishes between the macrobehavior of systems and the microprocesses within them (e.g., Holland, 2006; Kauffman, 1995; Mitchell, 2009), this model was proposed as a metatheory to reconcile divergent perspectives in the learning sciences (i.e., the cognitive vs. situative debate) and to guide the development of learning theory (Jacobson, Kapur, & Reimann, 2014). Alternatively, we align with Davis and Sumara's (2006) notion that a CS approach can "rise among" existing theory and research to provide insight into the multilevel, interactive nature of social and behavioral phenomena. We don't argue for CS as a pathway to a metatheory that harmonizes conflicting perspectives. Rather, we view CS as a way to bridge the gap between theory and method in cases where theory describes interaction dominant phenomena, or when the role and strength of relationships between variables shifts and changes over time in nonlinear ways (Richardson et al., 2014). Next we define an ontology of CS research derived from complex, dynamic, and emergent principles that serve as the defining characteristics of interaction dominant phenomena. We see these three principles as the foundation of a CS research paradigm in educational psychology that can bridge the gap between theory and research practices.

A Complex Dynamic and Emergent Ontology

Complex (Mitchell, 2009), dynamic (Koopmans, 2015), and emergent (Holland, 2006) characteristics of complex educational and psychological systems are lost in the translation of interaction dominant theories to component dominant models. The ontological characteristics of CS are compromised in research design for two primary reasons. The first is pragmatic. Technological constraints on data collection and analytic techniques have made empirical observation of complexity, dynamics, and emergence in social science domains extremely difficult (Strogatz, 2001). The second is philosophical. The prevailing paradigm in educational psychology is a linear approach that places a premium on nomothetic relationships (Kaplan et al., 2012). Researchers are trained and encouraged to design studies based on this paradigmatic worldview despite issues of feasibility and applicability to educational phenomena.

Off-the-shelf technologies for gathering intensive data have improved in recent decades, and advances in software packages have made new analytic techniques increasingly available to researchers. However, advances in technology that assist in gathering and analyzing intensive data that can be used to draw inferences about complex, dynamic, and emergent processes may be irrelevant if philosophically, educational psychologists don't accept an ontology of CS (Wan, 2011) research models that describe interaction dominant phenomena. As an alternative approach CS research has much to offer educational psychology: a different set of domain general ontological principles that describe the underlying mechanisms of complex phenomena. In the following sections we unpack the ontological characteristics of interaction dominant CS research models around the three guiding principles of complexity, dynamics, and emergence.

Complexity—Many definitions of complexity exist to describe the macrobehavior of CS in the social and natural sciences (Mitchell, 2009). There is no single definition of complexity; rather, complexity is defined in different ways in different contexts and fields of study. For example, there can be complexity of size and shape, complexity of logical depth, or complexity of entropy. Lloyd (2001) described three dimensions by which complexity can be measured: How hard is it to describe? How hard is it to create? What is the degree of its organization? The answers to these questions are not always obvious. Large objects aren't always more complex, nor are they always the most intricate. Mitchell (2009) used the idea of a string of letters as an example to illustrate the concepts of algorithmic and statistical complexity. The letters represent the emergent state of a CS as it changes over time, for example, the emotional state of an individual over the course of a day where each letter represents a different state. Imagine one string of letters, ABABAB, with 100 repeating pairs. The algorithmic information required to reproduce this pattern is simple, "Print AB one hundred times." It is easily reduced and easily described in macro and, as such, is low in complexity. Similarly, imagine another string of letters 100 characters long, this one created purely at random. It is also easily reduced statistically via "print a random string of letters one hundred characters long" and is easily described in macro. Accordingly, many definitions of complexity rely on the notion of some balance between order and randomness. This is the case within many social science fields, where complexity relies on what Gell-Mann and Llyod (1996) called "effective complexity," which is a combination of regularity and randomness in macrosystem behavior. The principle of effective complexity can be represented in many ways. Two common representations are in network structure and dynamic time series data. See Figure 2 for a graphical representation of effective complexity in a simulated dynamic times series and a simulated network.

The definitions of complexity that are perhaps most useful to educational psychology align well with the effective complexity of education relevant phenomena. For example, statistical complexity (Crutchfield & Young, 1989) is based on the amount of information about the past history of a system that is required to explain its future behavior. This approach relies on constructing a model of the system, based on its observed behavior, such that the model behavior is indistinguishable from the system's behavior. Akin to Gell-Mann's notion of effective complexity, statistical complexity is low for both highly ordered and highly random systems. Thus, CS require a large amount of information about past system behavior to produce a forecast about its future behavior patterns over a longer time horizon.

Complexity can also be defined as the degree of hierarchy within a system. All systems have a minimal hierarchical order or a whole that consists of related parts (Valsiner, 2008). Simon (1962) described the architecture of CS as their degree of hierarchy, or CS that are composed of subsystems, which are in and of themselves composed of subsystems (e.g., students and teachers make up classes, classes make up schools, schools make up districts, etc.). The idea is that the system is composed of building blocks, but each building block can evolve, or develop into new adaptive states, to become a new building block, the combination of which becomes another larger subsystem. In Simon's formulation, complexity can be measured in terms of the depth of the hierarchy as well as the near decomposability of the system. The complexity of the hierarchy is similar to the notion of the fractal, or self-similar patterns at all levels of the hierarchy. Near decomposability is the notion that there are many more strong interactions within subsystems than there are between. From this point of view, complexity involves both the networked nature of strong interaction within and between system components and the nested structure of the system as a whole, where nested interaction dominant systems are more complex. Together, these characteristics can be used to understand the complexity of a system.

Dynamics—Dynamics describes the microprocesses by which the component parts of a CS interact over time, both among themselves and in conjunction with the overall macro-behavior of the system. In dynamic microprocesses, component parts of the system change one another through interaction. As the component parts interact, a dependency among the components is created so that the behavior of individual components is constrained by the actions of other components. Thus, the change of the system behavior is partly the result of a self-organizing processes rather than deriving from some type of centralized control. In other words, the system behavior is partly governed by a bottom-up process that may look different at distinct points in time as the component parts organize and reorganize in a nonlinear fashion. Further, the process of organization and reorganization of the components is also partly shaped by the overall behavior of the system and the context in which the system operates (Witherington, 2015). Change behavior may be gradual or sudden, depending on the confluence of interaction among systems components, limits to behavior imposed by macropatterns of system behavior, and changes in the context surrounding the system. This type of interaction produces a discernible form of dynamic, nonlinear behavior that can provide insight into its complex functioning.

Dynamic complexity is a necessary condition for self-organizing behavior and adaptive change (Richardson et al., 2014). In contrast, loss of complexity over time, as evidenced by increased order or increased randomness in a measure of a system, is associated with the well-known concept of entropy. From an information perspective, entropy is described as the decline into disorder, or decomposition. For highly ordered or highly random systems, complexity is low. They do not decline into chaos, or ascend to increased order, or produce cyclical patterns oscillating between both. For systems in between, complexity is high. For in between educational and psychological systems, the ability to resolve into some type of partly stable, partly unstable equilibrium is treated as evidence for adaptive system function. In the letter string example just cited, an adaptive case would manifest both repeatable patterns and random strings of letters interlaced. Statistically this is akin to sequential dependence, or autocorrelation. Complex dynamic behavior can be observed in microgenetic time series data where many measures of the same variable(s) are taken in close proximity to one another over time (Chinn & Sherin, 2014; Siegler, 2007). It can also be measured in networks where measures of relationships between nodes (i.e., people or variables) form through collaboration or interaction. Identifying stable patterns that emerge in time intensive or relation intensive data, the conditions that lead to stability, and how robust a system is to disruptions (or perturbations) is central to studying the dynamics of a system.

The tendency for a system to settle into a stable pattern is called an attractor state (Abraham, Abraham, & Shaw, 1990). Attractor states are a way of describing homeostasis where the stability of a system is maintained through a series of continual adjustments to internal or external perturbations (Newton, 2000). Attractor states apply to all open, biological, thermodynamic systems that exchange heat, matter, or information and involve the consumption or production of energy. For example, one way to produce evidence of an attractor state is to observe variables at short intervals to create a time series. Measurements of variable combinations at a single time point can be treated as a vector. Each vector represents a state of the system at a single point in time. A collection of vectors can be treated as a state space, or all of the combinations of values for the system (Abraham et al., 1990; Hollenstein, 2013). A point or orbit around which the system tends to evolve is considered an attractor state and indicative of an emergent phenomenon. Component dominant systems that act in mechanical ways produce only one attractor state. For example, a pendulum produces a cycle or an oscillation. A CS, like a living organism or a group of people engaged in coordinated activity, can produce many attractor states. For example, Kaplan and Garner (2017) discussed stable motivational states such as performance-orientation as attractor states related to student role identity that emerge from the complex interaction among intra-person factors and contextual influences. Also, researchers who examine collaborative learning and team work describe group-level processes such as planning, reasoning, or decision making as attractor states with collective properties that emerge from the complex interaction of group members during collaboration (Arrow et al., 2000; Cooke, 2015).

Emergence—Emergence is the mechanism by which dynamic microinteractions of system components give rise to novel macro-system behavior (Holland, 2006). In the traditional philosophy of social science the term *mechanism* refers to a causal system where the relationship among system components is linear, reducible, and replicable (Cronbach & Meehl, 1955; Hempel, 1965). Using the formulation of traditional logic, if x can be reduced to set y, then set y is more basic than x, x is constituted by y and is nothing more than it. However, the philosophy of social science has been expanded to address the emergent characteristics of CS (Sawyer, 2004). The term *mechanism* is now commonly used in contrast to its use in logical empiricism (i.e., the 20th-century philosophical movement that sought a greater role for scientific methodology in shaping society) to explain interdependent relationships among system components and the properties that emerge from their interaction (Bunge, 1997; Hedstrom & Swedberg, 1998). A key defining factor is that the emergent macrostate has an ontological status that is separate from its realizing properties (Sawyer, 2004).

Some educational phenomena are reducible and others are not, and explanations about the composition of educational phenomena rely upon adequate distinctions between emergent phenomena and mechanical phenomena. Bar Yam (2003) described two forms of emergence. The first is his notion of emergent simplicity, such as the complexity of chemical interactions in a neuron cell that result in the simplicity of individual neuron firing to activate or inhibit other neurons. The second is an emergent complexity, where from the simple interactions between neurons the complexity of a brain emerges. One common sociological example is a church (Sawyer, 2004). The complex interactions among people, texts, and objects can emerge to what we understand as a church. Although in macro it is repeatable and recognizable, the concept of a church cannot be perfectly reduced to a stable set of microcomponents. Too, the cooperation and interference among churches can manifest a complex sociological environment replete with both harmony and disorder.

From this perspective many constructs in educational psychology take on the ontological qualities of emergent phenomena. Classrooms make up schools, schools make up districts, and so on. However, distinguishing them from component dominant phenomena is critical. To make this distinction, Sawyer (2004) argued that CS with emergent mechanisms produce *multiply realizable* complex macroconstructs via *wildly disjunctive* dynamic microinteractions (Fodor, 1974). If a latent construct can be described as emergent, as motivation, affect, engagement, epistemology, and learning often are, then interaction dominant relationships produce repeatedly identifiable, multiply realized attractor states. Thus, it would be impossible to define all combinations of components that produce an identifiable macrostate of a CS. To be a truly emergent mechanism, the identification of a precise set of interdependent interactions that can be delineated across time and context is impossible to pin down; that is, it is wildly disjunctive. For example, let's consider the generic concept of a successful student-centered lesson. If an unknowable combination of instructional strategies, student attributes, and environmental factors can produce what can repeatedly be identified as such a thing, then it is emergent. If a successful student-centered classroom can be perfectly reduced, it is mechanical. It is likely that many concepts and constructs in educational psychology are driven by emergent mechanisms.

Implications for Research

Improving the alignment between complex theory and research method in educational psychology requires a shift from component dominant to interaction dominant thinking about conceptual research models. At the heart of this shift is establishing complex, dynamic, and emergent CS ontological assumptions for educational psychological research. A CS ontology suggests that research requires a multilevel examination of dynamic processes that yield complex emergent phenomena. Dynamic processes function differently from context to context and are shaped by the macrocomplex, emergent behavior of the system. Thus, the dynamic qualities and interdependent relationships among variables, not summary differences, make meaning of system functioning. System self-organization and the emergence of attractor states, evidenced by effective complexity, are critical for understanding system behavior. Furthermore, choices about the context of investigation, the critical variables of interest, and time intervals of study shape understanding of the overall system of study. The assumptions inherent in a complex, dynamic, and emergent ontology of interaction dominant models require a set of methods and research designs that are not widely utilized in educational psychology. In the following sections we address CS research designs, methods, and some related equation-based analytic techniques.

CS RESEARCH DESIGN

Alignment between research questions, method, and analyses with respect to investigations of CS in educational psychology can help shift research from conceptual grounding to methodological execution. In a component dominant approach the research questions, data collection, and analyses are often formulated around a large number of variables and/or a large number of persons, but data are collected on a single occasion or on very few. Microgenetic change over time, and the quality of the relationships between persons is not regularly observed. To preserve the complex, dynamic, and emergent ontology of interaction dominant CS models, research should be formulated in a way that represents the changing and interdependent relationships among individuals and observations over time, as well as interactions amongst multiple levels of analyses. Accomplishing this requires intensive methods that can capture change in system elements and the relationships between them. Research questions should be formulated to address within element change over time and/or the dynamic interaction between elements. Related research designs and data collection can be intensive in three ways: *time intensive, relation intensive, or time-relation intensive*.

Time-intensive approaches are used to make inferences about system behavior using closely spaced observations over time. Closely spaced observations of a single variable taken from the system are used to examine microgenetic change and make inferences about macrosystem behavior. Relation intensive approaches are used to make inferences about the system behavior using measures of the dependent relationships between variables. Cross-sectional data that captures the relationships among all persons or variables that compose a system are used to examine the structure of the system and how and why relationships form and change. Time-relation intensive approaches are used to make inferences about system behavior using closely spaced, simultaneously collected observations of both within-element change and changing between element relationships. The observations are used to examine endogenous and exogenous effects on change within a system.

The interaction dominant ontological model offered in Figure 1 provides conceptual guidance for formulating CS research around these three intensive approaches. Three strategies may be helpful to researchers for deciding upon intensive methods to guide their research: (a) examine a single element from the center of a CS and study its dynamic, time-intensive behavior; (b) define a natural boundary for a CS and study the underlying, relation intensive structure; and (c) choose several critical elements from a CS and study their dynamic, time-relation intensive interactions (see Figure 3 for a summary of these strategies). These three approaches align with the intensive methods just described and should be driven by research questions about time-intensive, relation-intensive, or time-relation intensive processes.

Research Questions and Methods

Because the broad direction of research emerges from an iterative relationship between research questions and research methods, it is important to examine the characteristics of both that address complex, dynamic, and emergent properties. Research questions leading to CS methods and analyses are focused on time-intensive, relation-intensive, or time-relation intensive processes. Questions should correspond to data collection techniques that can provide evidence for interaction dominant processes. Next we outline the salient characteristics of CS research questions organized around time-intensive, relation-intensive, and time-relation intensive approaches. Because these are broad categories of research, there is no single prescribed way to carry out a specific approach. Accordingly, within each section we provide example studies that contain research questions in line with these approaches, as well as example studies that utilize aligned methods for collecting data.

Time-Intensive Questions—Time-intensive processes describe the dynamic change of individuals or variables in a system over time in nonlinear ways. Research questions that reflect time-intensive processes may focus on any unit of analyses undergoing a process that is expected to unfold over time. Change processes may be framed as investigations of intraindividual change, or the focal unit of analysis may be emergent processes or contexts that offer affordances for development (e.g., classroom structures, social partners) or the characteristics of collaborative groups. Although not an exhaustive list, time-intensive research questions may query the structure and shape of the change processes, how prior history affects subsequent behavior, how system memory constrains possibilities in change, how learning or social-emotional processes change in response to external environment perturbations, or how individual growth and change is influenced or governed by environmental constraints or affordances.

Extant studies in educational psychology that apply a CS approach tend to ask time-intensive research questions. For example, in their study on self-regulated learning during academic tasks, Garner and Russel (2016) framed two research questions. The first asked how patterns of visual attention shifted during a learning episode, whereas the second delved deeper into investigating dynamic structures in visual attention sequences and how these dynamics are shaped by contextual sensitivity to task characteristics. In another example, Stamovlasis and Sideridis (2014) conducted a study on self-regulation framed by research hypotheses about nonlinear changes in arousal during achievement situations (e.g., a class presentation) as bound by motivational perceptions. Koopmans (2015) examined short-term and long-term dependencies in high school attendance rates demonstrating that attendance is not the stable predictor of school success it is often portrayed to be.

Time-Intensive Methods—Methods for collecting time-intensive data range from the use of experience sampling techniques such as the use of diaries and surveys to the use of sensors and video recordings. What defines the method is the microgenetic observation of variables over time. Delignieres and colleagues (2004) used a specially designed piece of software to administer a self-esteem instrument twice a day for 512 days. Now, off-the-shelf applications for mobile phones and other electronic survey data collection methods make this type of time series data collection increasingly accessible to researchers, especially for so-called in-the-moment data collections, where data are collected in context, reducing the possibility of reflection bias. For example, Martin and colleagues (2015) collected motivation and engagement data three times a day, 5 days a week, for 4 weeks in a sample of 759 students to examine intraindividual variation. Another example of time-intensive data collection methods include the use of electrodermal activity (EDA) sensors, which measure microgenetic chemical changes in the skin due to physiological changes in emotion. Empatica (www.empatica.com) and Shimmer (www.shimmersensing.com) appeared to be the two most popular companies for manufacturing sensors for collecting EDA data in educational contexts. For example, Villanueva and colleagues (2014, 2016) took EDA measures to examine students' emotional states during an exam activity. They integrated survey measures with the galvanic skin response data collection. Analyzing the time series skin response data in conjunction with the survey data allows them to draw conclusions at multiple levels of analysis.

Relation-Intensive Questions—Relation-intensive processes describe the relationships or interactions among individuals or variables in a system. Research questions about relation-intensive processes focus on identifying the structure of the relationships in a system and the purpose and weight or value of exchanges. Relation-intensive questions may focus on interperson relationships, or the focal unit of analysis may be relationships between organizations or psychological constructs. Although not an exhaustive list, relation-intensive questions may focus on the underlying self-organized structure of a system, the individual characteristics of elements that predict relationship formation, the elements of a system that influences the flow of information throughout the system, and the communities that have emerged from interaction over time.

Examples of relation-intensive research questions in educational psychology tend to focus on person-to-person interactions including studies of peer relationships in schools (e.g., Shin & Ryan, 2014), collaborative teaching (e.g., Moolenaar 2012), and learning networks (e.g., Dou et al., 2016; Grunspan et al., 2016). In one example, Moolenaar and his colleagues (2012) framed research questions and hypotheses around dense school interactions at multiple levels of analyses. Specifically, they investigated how the characteristics of teachers' personal and expertise networks related to perceptions of collective efficacy and, in turn, how collective efficacy supported student achievement. Others have investigated how classroom interactions are affiliated with the development of student self-efficacy in physics courses (Dou et al., 2016).

Relation-Intensive Methods—Methods for collecting relationship-intensive data range from observations of behavior to analysis of existing documents and the use of surveys. Both interperson and intervariable relations can be targeted. A recent interperson example in educational psychology is an advice-seeking network among teachers in a school. Sweet (2016) used an electronic survey that asked teachers to identify from whom they solicited advice. The data were used to create a network representation of advice seeking, where nodes are the teachers and the edges indicate who seeks advice from whom. Similarly, Siciliano (2016) used an electronic survey to collect school network data to show how teacher self-efficacy is shaped by both beliefs and peer interaction. Using surveys or existing documents to map complex relationships between persons or schools and organizations has become increasingly common (e.g., Au & Ferrare, 2015). Relationship-intensive data can also be collected to examine the ties among psychological variables. For example, Fried and colleagues (2015) created a network model of responses to self-report depression inventories (i.e., Likert-type data) to model bottom-up relationships among depression indicators.

Time-Relation Intensive Questions—Time-relation intensive processes describe both within-and between-element changes over time. Research questions about time-relation intensive processes focus on microgenetic correspondence among social partners, individual and contextual elements, psychological constructs, or intergroup/organizational change over time. Time-relation intensive questions may focus on how individuals and their social partners reciprocally influence each other over time, how multiple psychological phenomena vary together, how group membership change over time, or how individuals influence change in group behavior, to name a few areas of inquiry.

For example, researchers have asked how individual and instructor factors continuously interact to influence student learning and how changes in learning influence shifts in interaction patterns (e.g., van Vondel, Steenbeek, van Dijk, & van Geert, 2016). Researchers have also investigated how interaction dependencies form between teachers and students during learning situations and asked questions about the cyclical nature of interactions and how classroom learning characteristics emerge from discrete moment-to-moment interactions (Pennings & Mainhardt, 2016; Turner, Christensen, Kackar-Cam, Trucano, & Fulmer, 2014). Shin and Ryan (2014) focused on changes in peer networks to investigate the relationships between social networks and academic outcomes, investigating how peer selection and influence processes were related to student motivation, engagement, and achievement over time. Kapur and colleagues (2008) identified participation inequality in problem-solving situations as a group property that emerged from the quality of early individual interactions.

Time-Relation Intensive Methods—Methods for collecting time-relation intensive data range from surveys to observations, video recordings, and sensors. For example, using observations of trials that examine child–caregiver interaction within varied contexts, Thelen and Smith (2003) provided an elegant investigation of how children develop object permanence. Pennings and Mainhard (2016) have conducted several studies of student–teacher interactions, coding classroom video recordings according to a 2 × 2 interpersonal framework. Similarly, Turner and colleagues (2014) operationalized student engagement as an interpersonal classroom activity, using classroom observations and state space models to identify instructional differences in patterns of classroom engagement. In another example, Stamovlasis (2016) framed his research on collaborative group functioning (interindividual processes) from a CS perspective, identifying patterns and structure in verbal interactions that give rise to behavioral outcomes at the macrolevel. He used discourse analysis to produce coded categorical time series data (i.e., a letter string) that described the functioning of collaborative groups (e.g., YN = expressing approval; N = expressing disagreement; D = expressing doubt to yield a time string such as YYNNDYNYDDNNY).

EQUATION-BASED ANALYTIC TECHNIQUES

A range of analytic techniques can be used to investigate CS research questions and study complex, dynamic, and emergent processes. In the quantitative realm, Parunak and colleagues (1998) distinguished between equation-based modeling and agent-based modeling for CS research. In agent-based modeling, the goal is to emulate the system by programming components (or agents) that follow behavioral rules, thereby producing emergent outcomes. In equation-based modeling, the goal is to evaluate a system using observations that are entered into equations. Both are based on the notion that two kinds of entities can be examined, individuals and observables, both with temporal resolution. For example, CS researchers from distinguished research centers such as the Santa Fe Institute and the New England Complex Systems Institute have made extensive use of computation-modeling techniques such as agent-based modeling and cellular automata that emulate the behavior of CS. Agent-based models have also been utilized in educational psychology research (Abrahamson & Wilensky, 2005). From a qualitative perspective, social cultural researchers often adhere to very similar epistemological assumptions as CS researchers and utilize longitudinal, thick descriptions to explain how systems function and change over time (e.g., Turner & Patrick, 2008). There are a variety of resources for those interested in these types of CS analytic techniques. Davis and Sumara (2006) provided guidance for complexity inquiry in education, laying the foundation for descriptive complexity research (i.e., providing clear description of CS phenomena such as self-organization) and pragmatic complexity research (i.e., identifying the conditions of emergence). Shalizi (2006) provided a thorough overview of CS science methods and techniques that have been widely utilized in the natural sciences. Wilensky and Rand (2015) provided a useful instructional primer on agent-based modeling techniques and applications that is friendly to social scientists.

Here we focus on nonlinear equation-based modeling techniques because they are perhaps closest to the types of methods that educational psychologists are familiar with. In the following sections, we provide an overview of three nonlinear equation-based techniques that can offer novel insight into interaction-dominant educational systems: nonlinear time series analysis, dynamic modeling, and network analysis. These three techniques may be attractive to educational psychologists because they can be used with data sources and data collection methods that are already widely utilized among researchers in the field. Each subsection is aligned with a strategy depicted in Figure 3. Rather than give a highly technical description, we provide a conceptual overview of the analytic techniques and related examples to demonstrate how they can be used. Each subsection begins with a review of the types of evidence that need to be collected to utilize a given technique. Then we provide some discussion about the analytic techniques themselves and various resources that contain in-depth technical description. We encourage readers to consider these methods and analytic techniques as viable for scholarship in educational psychology, either as primary analytic methods or in conjunction with more traditional methods.

Analyzing a Single Element Using Nonlinear Time Series Analysis

Overview—Complex dynamic systems involve the push and pull of interacting elements, many of which are unknowable, not directly observable, or infeasible to measure. Accordingly, researchers may be interested in examining the dynamic behavior of a single variable hypothesized to be at the center of a CS with the goal of making an inference about the overall functioning of the system itself. Because relationships among components are assumed to be interdependent, dynamic changes in a single critical variable contain information about the entire system (Takens, 1981). In one approach, a single dynamic signal (i.e., time series) can be analyzed using nonlinear time series analysis (Coco & Dale, 2014; Richardson et al., 2014; Riley & Van Orden, 2005). The goal is to use the dynamic qualities of a single variable to allow for inferences about the whole system. The characteristics of the signal can be used to reconstruct evidence of system functioning without the need to operationalize or measure all system elements. The researcher can identify contextual influences and constraints, or other critical values that produce complex, dynamic, and emergent characteristics. One example that helps to illustrate is the human heart (Lipsitz & Goldberger, 1992). The human heart produces complex dynamic signals when the body is healthy but overly ordered (e.g., congestive heart failure) or overly chaotic (e.g., atrial fibrillation) signals during pathology. It is at the center of a CS that is unknowable, but analysis of its dynamic functioning allows for inferences about the system as a whole.

Analytic Resources and Possibilities—Nonlinear time series analysis can be used to analyze dynamic behavior of system critical variables. The state of a system critical variable is measured at consecutive time intervals sensitive enough to produce a dynamic signal that contains iterations of system behavior. Nonlinear time series analysis is used to analyze the qualities of that signal to provide evidence that the variable is networked within an interaction dominant system. The characteristics provide information about the amount of regularity in the time series. Various research designs can be leveraged to produce insights into how contextual perturbations or contexts influence system functioning as described by the signals it produces. There are a variety of ways to approach nonlinear time series analysis depending upon whether the data collected are continuous or categorical, or numerical or textual.

Koopmans and Stamovlasis (2016) contained several useful applications, including examples of how to integrate time series analysis with hypothesis testing and linear analysis, and other examples such as the use of orbital decomposition (a technique for nominally coded time series data). Riley and Van Orden (2005) wrote a helpful primer on the topic, and time series analysis is common in engineering and the natural sciences (e.g., Gao et al., 2007). The American Psychological Association also sponsors a helpful advanced training for nonlinear methods conducted by the Center for Action and Perception (2016). Recurrence Quantification Analysis, Categorical Recurrence Quantification Analysis, Fractal Time Series Analysis, and Phase Space Reconstruction are common methods covered in the training (Center for Action and Perception, 2016). Further, Hamaker and Wichers (2017) described an approach to time series analysis called dynamic multilevel modeling, where a time series model at Level 1 describes the within-person process, whereas between-person differences in the dynamic features are modeled at Level 2.

Analyzing Bounded Systems Using Network Analysis

Overview—Researchers may also be interested in defining the natural boundaries of a CS and analyzing its underlying structure at a given moment. The underlying structure of a CS is a network, and quantified networks contain the artifacts of dynamic, self-organizing properties. Network analysis allows researchers to test multiple levels of analysis simultaneously by examining the self-organizing processes of CS that may not be directly observable (Lusher et al., 2012; Watts, 1999). These tests allow for the examination of both micro- and macrolevel processes and artifacts of the evolution of structural changes within a system. Social Network Analysis and related techniques based on graph theory (Barabási & Albert, 1999; Erdös & Rényi, 1959) such as Quadratic Assessment Procedures and Exponential Random Graph Modeling (Goodreau, Handcock, Hunter, Butts, & Morris, 2008; Goodreau, Kitts, & Morris, 2009) are becoming more common in educational research. In addition, other approaches such as Ecological Network Analysis (Borrett & Lau, 2014; Laua et al., 2015) and Mixed Graphical Models (Haslbeck & Waldorp, 2015) have been developed to examine general systems applicable to networks that contain continuous, count, and/or categorical data.

Analytic Resources and Possibilities—No matter the approach, all networks are graphs composed of nodes and edges. In education research, nodes can be used to represent variables such as people or psychological constructs, and the edges represent the presence of a relationship or the exchange of energy or information. At its best, network analysis allows researchers to simultaneously examine endogenous and exogenous effects within interaction dominant contexts, or how system structures influence nodal attributes and vice versa. Researchers typically examine ego networks (a focus on a single node and the immediate relationships) or census networks (a focus on all possible relationships among nodes in a given bounded context). Networks can be directed or undirected (i.e., whether the direction of a tie is specified) or weighted or unweighted (i.e., whether the value of a tie is specified). Network analysis can be broken down into four specific levels (Borgatti & Ofem, 2010; Krackhardt, 1988; Scilliano, 2016). At Level of Analysis 0, the researcher is focused on the whole network, such as its density or network centrality. At Level of Analysis 1, the researcher is focused on the network nodes and their position within the network. At Level of Analysis 2, the researcher is focused on dyadic relationships in the network. At Level of Analysis 3, the researcher is focused on choice and influence and/or external perceptions of the network. External perception may include accuracy of outsider's mental models of the network, or cognitive social structures (Krackhardt, 1987).

There are a multitude of instructional primers and resources for learning network analysis, the extent of which go well beyond what can be explicated here. Sweet (2016) and Grunspan et al. (2014) have written excellent primers on social network analysis within educational contexts. And because R is perhaps the most popular software for conducting network analysis, many instructional materials for R packages, for example, Social Network Analysis (Butts, 2016); Mixed Graphical Models (Haslbeck & Waldorp, 2015), Ecological Network Analysis (Borrett & Lau, 2014), and network visualizations (Csárdi & Nepusz, 2010), are helpful for those interested in pursuing network analysis further.

Analyzing Several Elements Using Dynamic Modeling

Overview—Researchers may also be interested in the dynamic relationships among multiple system critical variables, where changes in one variable may influence changes in others, and vice versa. Researchers may be interested in describing relationships between the current state of a system critical variable and how it is changing, or how a variable changes in response to another variable, or how a variable changes in response to changes in other variables. Using nonlinear dynamics (Abraham et al., 1990; Hollenstein, 2013; Richardson et al., 2014; Strogatz, 1994), researchers can examine how multiple system critical variables change together over time. There are two main types of dynamic systems equations: differential equations (for modeling continuous time) and difference equations (for modeling discrete time). The dynamic relationships among variables are described in terms of their *state space*, or all the possible points or pairs of the values (i.e., vectors) for a given set of time series observation. Time is represented in the *phase space*, or a plotting of the trajectory created by the changing relationship between the two variables over time. Relationships that emerge from the dynamic interaction describe emergent system behavior in macro. Inspired by the foundational work of Waddington (1942), possible stable systems states are described as attractors. A geometric approach to analysis of attractors allows researchers to understand under what initial conditions, or intensity of perturbations, a system will remain stable or phase transition into alternative attractor states.

Resources and Possibilities—Dynamical modeling (Abraham et al., 1990; Hollenstein, 2013) can be used to provide evidence for how multiple variables in a system change together over time and form possible emergent attractor states. Similar to nonlinear time series analysis, the state of system critical variables are measured at consecutive time intervals (often within nested time scales) sensitive enough to produce dynamic signals that capture iterations of system behavior. The result of the analysis is patterns that describe the long-term behavior of a system. Dynamical systems models have been popular in developmental psychology for some time (Thelen et al., 1994), which offers excellent resources. Also, catastrophe theory has become increasingly popular among education and psychological researchers (Chow, Witkiewitz, Grasman, & Maisoto, 2015; Sideridis & Stamovlasis, 2016). Rooted in differential equations, catastrophe models can be used to determine how continuous changes in system control parameters (independent variables) can result in discontinuous changes, or sudden shifts between attractors states in outcome variables such as how changes in motivational valence disrupt the self-regulation process (Stamovlasis & Sideridis, 2014).

Furthermore, Hollenstein (2013) wrote a helpful primer on how to use state space analysis to study the interaction of two people in settings for use with Gridware software (Lamey, Hollenstein, Lewis, & Granic, 2004). Deboeck (2013) illustrated how derivatives can be integrated into structural equation analysis to model continuous time. Abraham and colleagues (1990) provided what they call a “visual approach” to the study of dynamic systems in psychology that is accessible to readers with a basic understanding of algebra. Strogatz (1994) also wrote a very helpful primer on nonlinear dynamic systems in the natural sciences that is accessible to those with a basic understanding of calculus. Work in food webs that capitalizes on predator–prey models (e.g., Pimm, 2002) has also been helpful to the authors for understanding how to expand the technique to educational contexts. There are a variety of ways that researchers can approach nonlinear dynamical modeling to examine educational systems. Educational psychologists who incorporate contextual factors into their models of motivation, engagement, and cognition may be able to leverage dynamical systems approaches to provide additional explanatory power to their models, especially with regard to how context shapes the activation of concepts, epistemologies, or other psychological states.

SOME FUNDAMENTAL TOPICS FOR CONSIDERATION

There are several topics that we see as foundational to the integration of CS research in educational psychology that can be investigated using the methods just described. These topics are specific to the principles of CS research and may be examined using mixed methods in ways that include the integration of hypothesis testing, linear statistics, and qualitative data with nonlinear techniques. They include (a) establishing context for levels of analysis and multiple time scales of a system of interest, (b) examining the change in complexity of educational systems, and (c) studying the decentralization and (de)differentiation of learning and psychological processes. Each of these ideas builds on the next and can be considered critical aspects of developing a CS research agenda or study.

Multiple Time Scales and Levels of Analysis

An important first step for CS researchers in educational psychology is to map the context for levels of analysis and multiple times scales of systems of interest. A CS unfolds over time and can span many levels of analysis. Taking time and context seriously involves the integration of multiple levels of analysis and time scales that are useful or meaningful to the researcher. Models should include a hierarchical conceptual mapping (e.g., persons, within classrooms, within schools) and spacing of measurement points (e.g., moments, days, weeks) to determine the conceptual and temporal resolution of interest for a given system. Multilevel time scale maps are an important precursor to defining the context for levels of interest, critical variables at each level, and time scales for measurement, allowing researchers to develop studies that are more sensitive to change processes. They are central to preserving the complexity of theory, generating sound research questions, and developing research designs that lead to the collection of intensive data. They can also lead to a more complete understanding and theorizing about the behavior and properties of a system and how those might change over time in reaction to perturbations or interventions.

Change in Complexity and System Functioning

Another important goal for CS researchers in educational psychology is developing evidence for the interaction dominant dynamics of systems of interest. A critical property of every CS is its capability to self-organize the interactions among components to meet task demands

(Vaillancourt & Newell, 2002). Evidence for self-organization can be demonstrated through a balance of randomness and order in macrosystem behavior, or effective complexity. A concept known as the Change in Complexity Hypothesis suggests that self-organizing properties of a given system allow for adaptive assembly, or the stabilization and dismantling of synergies between elements in a system. Adaptive assembly ensures efficient informational exchanges within and between systems through interdependent regulation processes. Increases in the amount of randomness or order in a system can be examined to test changes in complexity and draw inferences about adaptive system functioning. It is not clear at what level of measurement complexity and self-organization begin to emerge within complex time series data and transitive network structures when examining motivation, engagement, cognition, and learning. Establishing multilevel time scale maps and using intensive data to examine change in complexity in educational systems through the analytic techniques just described can lead to insights into the conditions and levels of analysis and granularity of data collection at which evidence for adaptive assembly emerges. Testing change in complexity hypotheses in educational systems can provide information about contextually specific influences and constraints that lead to adaptive system functioning. Examination of the ability of a system to resist and recover from perturbations, and what the dynamic patterns of resistance and recovery are, can provide context specific information about educational psychological theory and principles.

Decentralization and Differentiation in Theoretical Models

A final important goal is to examine how the strength, direction, and structure of systems change over time and context to context. At the heart of effective complexity is an interaction dominant structure. However, many educational psychological theories are rooted in information-processing theory and make strong assumptions about the role of centrally controlled processes (so-called common cause models). They are phenomenological in nature, placing a premium on the serial, centralized way humans tend to experience reality, as opposed to the decentralized, nested, self-organizing nature underlying experience (Ellis & Newton, 2000). The role of variables in common cause models, and the strength and structure of their relationships, is assumed to be static. Observed differences between individuals are often modeled as latent variables. Learning theorists often position knowledge and concepts as things or structures possessed by individuals, and many theories of motivation, engagement, and cognition incorporate executive function or appraisal processes as stable and central to system input and output. Yet much of the intra- and interperson phenomena that educational psychologists study is, theoretically, interdependent and interaction dominant, meaning the role, strength, and structure of relationships shifts and changes to adapt to both context and internal changes within a system. Research that examines contextually differentiated roles of system components, or how perturbations and development leads to dedifferentiation (i.e., where consolidation of system components can change system functioning) is rare. CS research that examines decentralization and (de)differentiation may provide insight into such things as how it happens that a person experiences a certain psychological state at a particular moment in a specific context but not in others, or how individual history interacts with immediate context to prompt the emergence of particular knowledge activation patterns.

FINAL REMARKS

CS research can provide a powerful strategy for investigating core phenomena in educational psychology, but deep consideration of ontological assumptions, theoretical and conceptual models, research questions, data characteristics, and possible analyses is required, and key challenges need to be considered, vetted, and adopted. Integrating CS research into educational psychology may require more flexible thinking about research methods, particularly with regard to significance testing, commensurate forms of data, and generally what counts as sound evidence within empirical research. Researchers and reviewers need to be open to new forms of evidence that describe context-specific patterns of interaction and be mindful of how to integrate new methods and analytic techniques with existing theory and method. This openness may begin with education and training in CS theory, methods, and analytic techniques in graduate-level educational psychology and learning science programs, as well as interdisciplinary research partnerships that transcend traditional boundaries. If we acknowledge that many of the intra- and interperson core phenomena we study in educational psychology have complex qualities that emerge from dynamic interdependent relationships among a multiplicity of factors, then CS approaches to research in educational psychology have much to offer. CS approaches can rise among existing research by aligning educational psychology theory with interaction dominant models and related methods and analytic techniques. In turn, these findings can be used to make inferences about dynamic interactions that give rise to structure, stability, and change within complex educational psychological systems, providing a more complete picture of learning in context.

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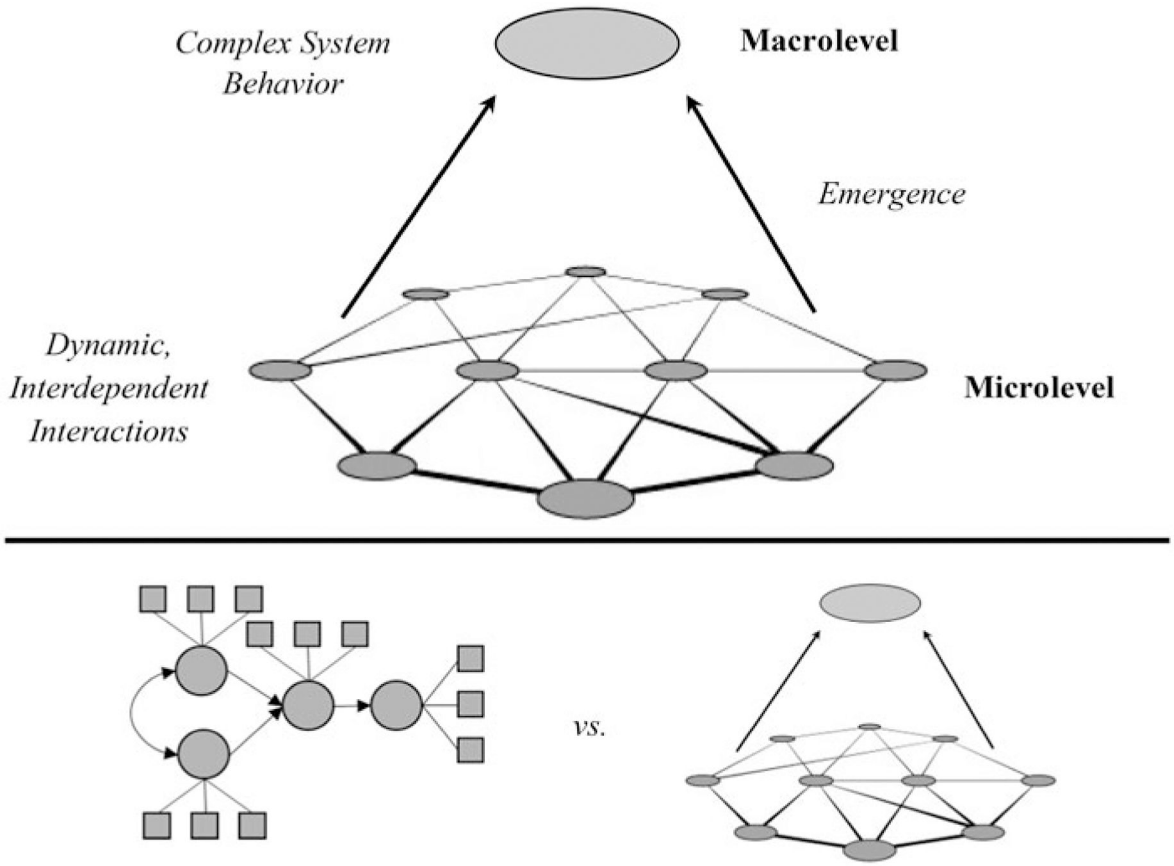

FIGURE 1.
Graphical representation of an interaction dominant model and comparison to a component dominant model. Note. The upper portion of the figure contains a graphical representation of an interaction dominant system. The network represents a softly assembled system. The gray oval at the top represents an ontologically distinct, macrolevel of analysis that emerges from the interaction of microsystem components. The lower portion of the figure contains a comparison of a generic component dominant system (left side) to an interaction dominant system (right side). The figure is meant to provide a gestalt for understanding the difference between the two types of models.

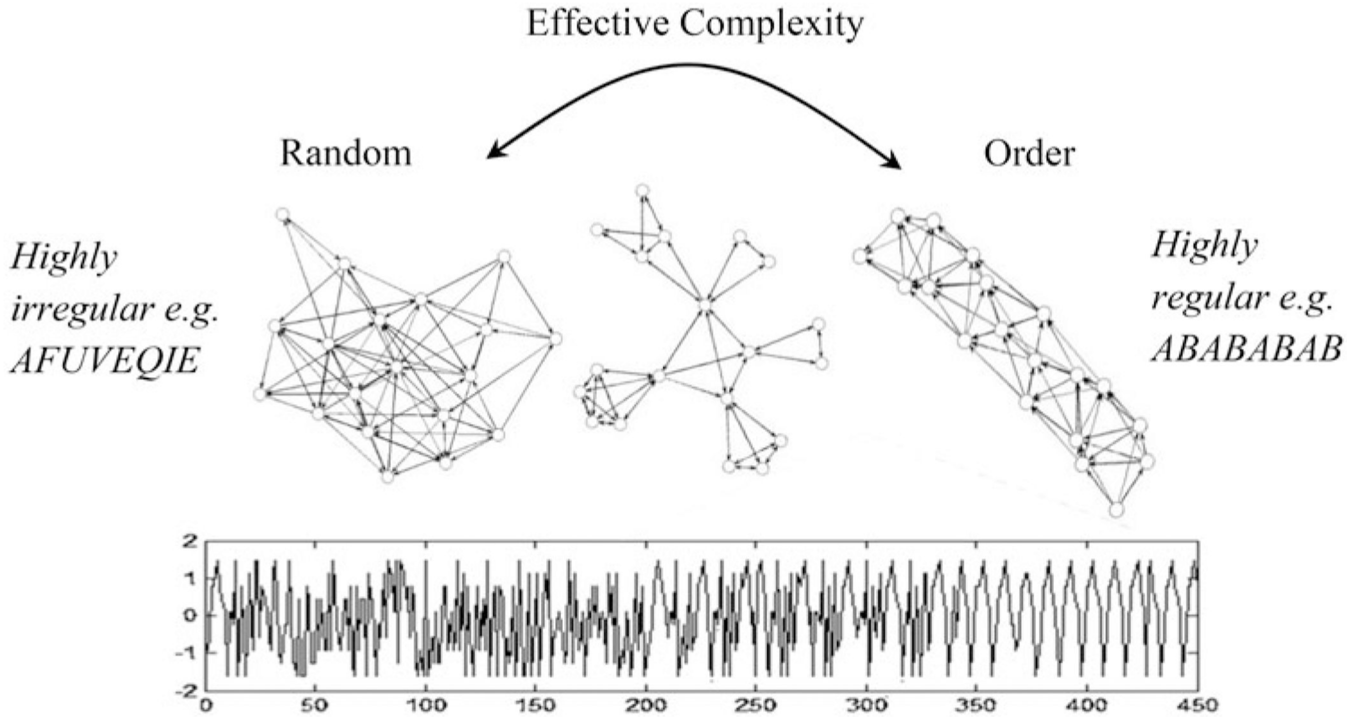

FIGURE 2.

Effective complexity in networks and dynamic time series data. Note. Center network graph shows aggregate collaborative relationships (edges) among students (nodes) during a 90-min class period (data gathered for an unpublished pilot study). Left and right network graphs are perfectly ordered (i.e., a lattice) and perfectly random (i.e., Bernoulli process) simulations of the observed data calculated using the Social Network Analysis package in R. Graph layout was produced using a forced atlas algorithm. The dynamic signal was simulated to illustrate the random, complex, and ordered types of fluctuations in the degree distribution (i.e., number of collaborative partners) of a single node in the network over time ranging from ordered to chaotic. The time scale for the time series is arbitrary and frequency reflects a z-transformation of possible degrees from the observed graph distribution. The network in the center of the figure and the middle portion of the time series illustrate the balance between randomness and order described in the principle of effective complexity.

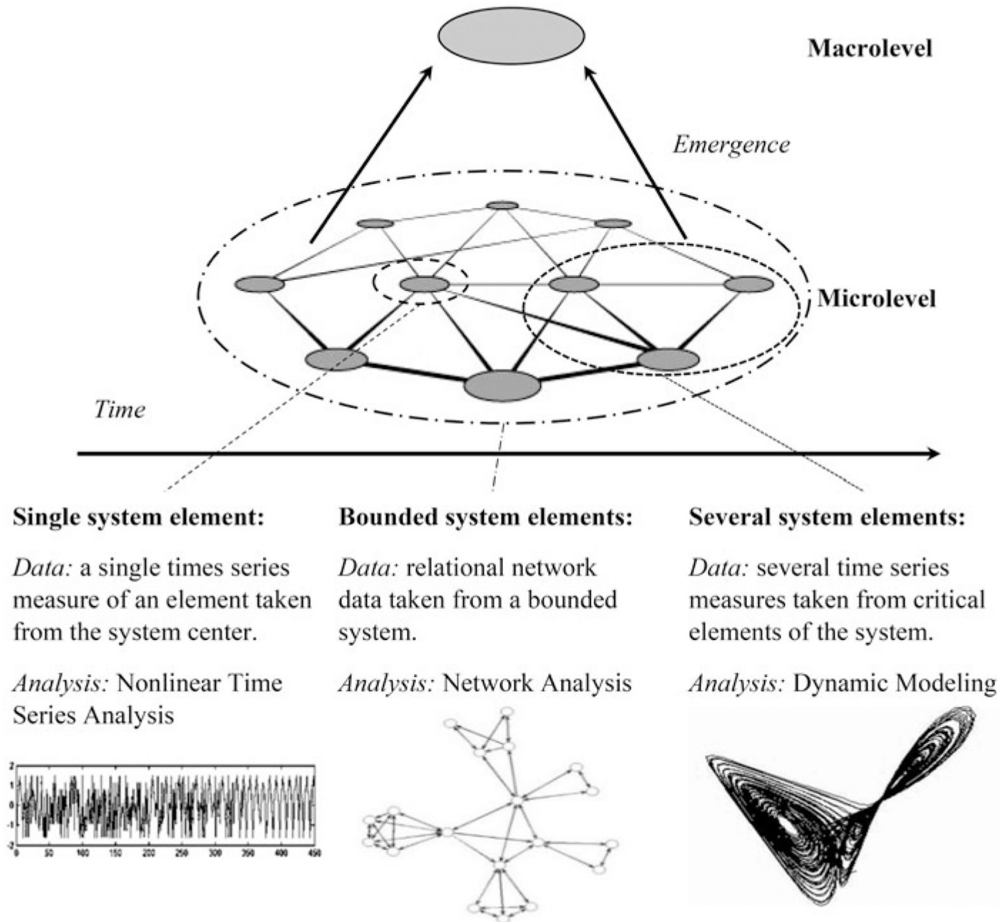

FIGURE 3.

Characteristics of complex systems that guide analytic choices about analysis. Note. The figure demonstrates three strategies for observing and analyzing complex systems: taking a single observation from the center of the system, taking several measures from a system, or arbitrarily bounding an entire system. Network and time series graphs (bottom left and center) were generated as described in Figure 2. The attractor state (portrayed in the bottom right of the figure) is a strange attractor simulated in MATLAB using a GUI provided by the Center for Action and Perception (Center for Action and Perception, 2016).