Organizational Research Methods
16(4) 581-615

DOI: 10.1177/1094428113493119
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Advancing Multilevel Research Design: Capturing the Dynamics of Emergence

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Abstract

Multilevel theory and research have advanced organizational science but are limited because the research focus is incomplete. Most quantitative research examines top-down, contextual, cross-level relationships. Emergent phenomena that manifest from the bottom up from the psychological characteristics, processes, and interactions among individuals—although examined qualitatively—have been largely neglected in quantitative research. Emergence is theoretically assumed, examined indirectly, and treated as an inference regarding the construct validity of higher level measures. As a result, quantitative researchers are investigating only one fundamental process of multilevel theory and organizational systems. This article advances more direct, dynamic, and temporally sensitive quantitative research methods designed to unpack emergence as a process. We argue that direct quantitative approaches, largely represented by computational modeling or agent-based simulation, have much to offer with respect to illuminating the mechanisms of emergence as a dynamic process. We illustrate how indirect and direct approaches can be complementary and, appropriately integrated, have the potential to substantially advance theory and research. We conclude with a set of recommendations for advancing multilevel research on emergent phenomena in teams and organizations.

Keywords

multilevel research, computational modeling, quantitative research, time series, research design

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The nature of the linkage between lower level entities and higher level collectives in concrete (i.e., physical) and abstract (i.e., social) systems has been theorized by philosophers, psychologists, and sociologists for over a century (Corning, 2002; Katz & Kahn, 1966; Sawyer, 2001). Indeed, in an effort to grapple with this complexity, the disciplines that compose organizational science have sliced the system into distinct levels—micro, meso, and macro[1]—that have been, at least historically, each associated with different disciplines and research methods (Roberts, Hulin, & Rousseau, 1978). Yet there is reasonable consensus across disciplines that two fundamental processes span the multiple levels of organizational systems: (a) top-down, contextual effects whereby higher level phenomena constrain, shape, and influence different lower level phenomena (i.e., cross-level effects) and (b) bottom-up emergence whereby dynamic interaction processes among lower level entities (i.e., individuals, teams, units)—over time—yield phenomena that manifest at higher, collective levels.

Empirical research designed to study these phenomena can be conducted using qualitative or quantitative methods. Arguably, qualitative methods, largely used by sociologists, have been at the forefront of efforts to describe the systemic character of social behavior in organizations and the "behavior" of these collective entities (e.g., Burns & Stalker, 1961; Emery & Trist, 1960). Indeed, until recently, empirical research encompassing the reciprocal complexity of contextual and emergent effects was largely limited to qualitative treatments (e.g., Barley, 1986; Orlikowski, 1992; Orlikowski & Yates, 2002). Quantitative research methods were simply not up to the task. That has changed. The development of a multilevel paradigm—an integration of theoretical principles, research design and measurement, and analytics—for investigating systems phenomena in organizations is an important quantitative research advance.[2] Early multilevel pioneers recognized the shortcomings of an organizational science based on systems conceptualizations that failed to directly study the linkages connecting distinct levels of analysis—micro, meso, and macro (House, Rousseau, & Thomas, 1995; Klein, Dansereau, & Hall, 1994; Roberts et al., 1978; Rousseau, 1985). Multilevel research has been spurred by the development of metatheoretical principles to guide theory building (Kozlowski & Klein, 2000), creation of frameworks to guide multilevel construct conceptualization and measurement (Bliese, 2000; Chan, 1998; Chen, Bliese, & Mathieu, 2005; James, 1982; James, Demaree, & Wolf, 1984; Kozlowski & Hattrup, 1992; Kozlowski & Klein, 2000; LeBreton & Senter, 2008; Morgeson & Hofmann, 1999), and evolution of analytics to enable appropriate modeling of multilevel phenomena (Bryk & Raudenbush, 1989, 1992; Burstein, 1980; Hofmann, Griffin, & Gavin, 2000; Muthen, 1994). Although all the conceptual, measurement, and analytical challenges are not resolved, in a relatively short time span, quantitative multilevel research has pushed beyond purely metaphorical treatments of "organizations as systems" (Kozlowski & Klein, 2000) to yield empirical knowledge that bridges multiple levels of the organizational system together (Mathieu & Chen, 2011). This is an important scientific advance.

This advance, however, is not fully realized because extant quantitative research is primarily focused on only one of the two core processes that cut across system levels; thus, it is incomplete. The vast majority of multilevel research is focused on top-down, cross-level effects, whereas emergence *as a bottom-up process* is largely neglected by quantitative investigators (Cronin, Weingart, & Todorova, 2011; Kozlowski & Chao, 2012a). There are two primary reasons for this state of affairs. First, when emergence is considered in multilevel research, it is primarily treated as part of measurement and construct validation for indicators that transcend levels (i.e., constructs that are measured at a lower level but are aggregated to represent a higher level). These are, of course, critical concerns. However, this primary focus yields a treatment of emergence in terms of theoretical assumptions that are—at best—indirectly supported by statistical indicators and conceptual arguments. Emergence as a dynamic process is not examined directly in extant quantitative research.

Second, there are substantial research ambiguities with respect to assessing and representing emergent phenomena. How do we study them? For emergent constructs, there are conceptually based measurement and construct validation models (Bliese, Chan, & Ployhart, 2007; Chan, 1998; Chen et al., 2005; Chen, Mathieu, & Bliese, 2004; Kozlowski & Klein, 2000) and well-accepted "rules of thumb" with associated statistical justifications (e.g., Bliese, 2000; James, 1982; James et al., 1984; Kozlowski & Hattrup, 1992; LeBreton & Senter, 2008) to support data aggregation from lower level measurement to higher level representation. For emergence as a substantive phenomenon, however, research guidance is quite limited. Moreover, emergence is complex because it incorporates both process (i.e., dynamic interactions among entities) and structure (i.e., over time it manifests as a collective property, a construct or "emergent state"). This duality of process and structure is fundamental to social psychological and sociological phenomena in organizations (Allport, 1954; Giddens, 1979; Katz & Kahn, 1966), but it makes a substantive focus on emergence a difficult fit to the commonly used quantitative research designs and methods in organizational science.

The purpose of this article is to advance more direct, dynamic, quantitative research methods for investigating emergence. Lest our purpose be misinterpreted, it is important to highlight some caveats. First, we are not proposing that the approach we advance is the only way to study emergence. It is one potentially powerful way, but one among many (e.g., intensive longitudinal designs, experience sampling methods could be adapted to study emergent phenomena). Indeed, as we will make clear, qualitative researchers have been studying emergence directly for decades. We wish to advance *direct quantitative research* on emergence. Second, our intent is not to supplant research that examines cross-level effects; such research is fundamental and remains important. Rather, our intent is to supplement it by urging quantitative researchers to investigate the other fundamental system process that is currently neglected. Third, our encouragement for direct quantitative research on emergence is not intended to suggest that attention devoted to assumptions of emergence in measurement development is misguided; such attention is essential. Rather, our effort is intended to expand the array of quantitative research design tools, push multilevel research in new directions, and advance direct investigation of organizations as multilevel, dynamical systems.

We begin by discussing the nature of emergence. The term has been applied broadly in the organizational literature in ways that are not equivalent. Indeed, some uses of the term are antithetical (Corning, 2002; Epstein, 1999). Explicit attention to conceptualization is critical. Drawing on complexity theory, we define emergence as a dynamic, interactive process and specify three core conceptual foci to capture its essential nature: It is multilevel, process oriented, and temporal. We then describe research design approaches that address emergent phenomena. We broadly characterize these approaches as indirect or direct, implemented by qualitative or quantitative research methods. Indirect approaches rely on retrospective observations and infer the nature and manifestation of emergence. Direct approaches rely on prospective observations that capture the process and manifestation of emergence as it unfolds. Most quantitative research is indirect because it infers emergence, whereas the vast majority of extant efforts to investigate emergence directly are qualitative (Kozlowski & Chao, 2012a). Qualitative research provides a rich descriptive foundation for theorizing about the process mechanisms that undergird emergence. However, quantitative research is needed to advance theoretical precision, verification, and extension. Our focus is on advancing quantitative research methods for investigating multilevel emergence directly.

We then illustrate how extending quantitative research to examine emergence directly can advance theory and understanding. It is not our intent to be exhaustive; that is beyond the scope of a single article. Rather, our intent is to explicate and illustrate; to provide exemplar topics for new research and a research approach that can be exploited to extend and build multilevel theory on emergence. We focus on three topic areas of team research—team perceptions, group decision making, and team interaction processes—that could and *should* focus on emergence as a process, but do not. Team research, at the meso juncture of micro and macro influences, is an ideal focal point for research on emergent phenomena. For each topic, we (a) describe the conceptual foundation with respect to emergence, (b) consider treatment of the topic in extant research highlighting that emergence is relevant but not directly addressed, (c) discuss new research foci that could be advanced if emergence was a focal substantive phenomenon, and (d) explicate how a more balanced research approach that integrates computational modeling/agent-based simulation with longitudinal research designs conducted in the field or laboratory can advance a more direct assessment of emergence and can facilitate theory building. We conclude the article with a discussion that provides a set of recommendations to help guide researchers who are interested in implementing and extending this integrated multilevel research design.

Emergence in Organizational Research

The Nature of Emergence

Definition. Kozlowski and Klein (2000) define multilevel emergence in organizational behavior as a bottom-up process whereby individual characteristics and dynamic social interaction yield a higher level property of the group: "A phenomenon is emergent when it originates in the cognition, affect, behaviors, or other characteristics of individuals, is amplified by their interactions, and manifests as a higher-level, collective phenomenon" (p. 55). Kozlowski and Klein were explicit in connecting their definition to complexity theory conceptualizations of emergence. Also rooted in complexity theory, Crutchfield (1994) noted that "some of the most engaging and perplexing natural phenomena are those in which highly structured collective behavior emerges over time from the interaction of simple subsystems" (p. 516), Axelrod (1997) stated that "the large scale effects of locally interacting agents are called 'emergent properties' of the system" (p. 4), and Epstein (1999) defined emergent phenomena as "stable macroscopic patterns arising from the local interaction of agents" (p. 53). In sociology, the "individualist emergentist" perspective (Sawyer, 2001, p. 563) represents a similar conceptualization, such that system-level behavior is "an emergent consequence of the interdependent actions of the actors who make up the system" (Coleman, 1986, p. 1312).

The concept of emergence has a long history of usage in philosophy and science. We emphasize the complexity theory conceptualization of emergence as a bottom-up process of dynamic interaction because it departs from alternative uses of the term *emergence* in the literature. According to Corning (2002, pp. 18-19), who cited Blitz (1992) as the source, "the term 'emergent' was coined by G. H. Lewes" circa 1874. The term is used to refer to a variety of distinctly *different* concepts, which—not surprisingly—has sown seeds of confusion. One use of the term refers to the mere appearance, growth, or manifestation of a phenomenon (e.g., Pickering, 1993). Lacking any systems character, this conception is not relevant to multilevel emergence (Corning, 2002). Another much more problematic distinction concerns the nature of the linkage between micro and higher levels, an issue of the relation between "wholes" versus "parts" (Chalmers, 2006; Corning, 2002; Sawyer, 2001). Referring to this distinction, Sawyer (2001) noted that "sociological uses of emergence are contradictory and unstable; two opposed sociological paradigms both invoke the concept of emergence and draw opposed conclusions" (p. 552). Indeed, these differing conceptualizations of emergence and the nature of the micro–macro linkage are an ongoing source of debate in sociology (e.g., Greve, 2012).

With respect to these differing conceptualizations, general systems theory (von Bertalanffy, 1968) describes emergent phenomena as holistic, greater than the sum of the parts, and irreducible. Similarly, classical emergentism in philosophy views emergent phenomena as "unexplainable in principle" by reference to lower level entities (Epstein, 1999, p. 53).[3] In sociology, collectivist theories view emergent phenomena—though acknowledging their origin in individual interaction—as holistic, independent, and nonreducible at the higher level (e.g., Blau, 1987; Durkheim, 1895/1964). This view is not consistent with our complexity theory conceptualization of multilevel emergence. It is also inconsistent with other sociological accounts that assume micro origins for the properties of social collectives (e.g., Coleman, 1987; Hayek, 1942; Homans, 1958; Mill, 1843; see Sawyer, 2001). From our perspective, the issue is not one of reductionism, that is, of deducing the properties of macro phenomena from their micro origins. Rather, the issue is to deduce the *process mechanisms* inherent *in micro interaction dynamics* that yield the higher level phenomenon. As Kozlowski and Klein (2000) expressed it, "We wish both to understand the whole *and* keep an eye on the parts" (p. 54). The goal is to understand the process of emergence through system dynamics across multiple levels—simultaneously.

Note that although the Kozlowski and Klein definition focuses on micro and meso levels, phenomena can originate at other levels and emerge to one or more higher levels. Ployhart and Moliterno (2011), for example, theorize on the emergence of human capital across multiple organizational levels, and Kozlowski, Chao, and Jensen (2010) theorize about organizational learning as a process of emergence across the micro, meso, and macro levels of the system. Nonetheless, the meso level suits our focus, as teams sit at the juncture of micro origins and more macro contextual constraints; it is an ideal target for the study of emergence (Kozlowski & Chao, 2012a). Another point to note is the duality of process and structure in emergence highlighted previously. The process of emergence begets structure in the form of an emerged phenomenon that then shapes subsequent processes (Allport, 1954; Giddens, 1979; Katz & Kahn, 1966). Finally, Kozlowski and Klein (2000) argue that a given phenomenon, although it is not explicit in the definition, can emerge in different ways or forms; the dynamic process by which a phenomenon emerges need not be universal in form.

Core Conceptual Foci. Our definition incorporates conceptual foci that are useful to make explicit, as they will later be used to establish that typical designs used in quantitative organizational research fail to address emergence directly (see Figure 1). First, emergent phenomena are *multilevel*. They encompass at least two different levels of analysis, a lower level at which the phenomenon originates (e.g., individual cognition, motivation/affect, and behavior) and a higher level at which the collective property manifests. Second, emergent phenomena are *process oriented*. The substantive emphasis is on the process mechanisms that drive the dynamic interactions among entities (e.g., individuals) that yield the emerged property. The process mechanisms are the theoretical engine of emergence; thus, they need to be specified with precision. Third, emergent phenomena *take time to manifest* at the higher level. Time frames may be very brief or quite lengthy, depending on the phenomenon. Finally, although it is not a core characteristic of emergence per se, contextual factors at the higher level shape and constrain the process dynamics of emergence. Thus, the context is a critical consideration in conceptualizing how emergence may unfold.

Challenges to Studying Emergent Phenomena. Although it is easy to conceptualize how individuals shape group processes and outcomes, conducting research that examines this has been problematic in multilevel research (e.g., Griffin, 1997). Indeed, all major treatments of multilevel and latent growth modeling (LGM) acknowledge the inability of current analytical methods to determine the effect of a lower level unit on the higher level construct (Goldstein, 2003; Heck & Thomas, 2000; Kline, 2005; Raudenbush & Bryk, 2002; Singer & Willet, 2003; Snijders & Bosker, 1999). The software packages used to conduct multilevel analysis cannot provide these estimates (e.g., SPSS, HLM, MLwiN; Croon & van Veldhoven, 2007). The basic conundrum is that individual influence is bound up in the interactive processes of emergence.

Researching emergence provides a window to begin mapping how such processes function. However, there are significant challenges to studying it. First, emergence as a process has received only limited theoretical attention in multilevel research. The observational flexibility of qualitative research provides one window for theory building (e.g., Orlikowski, 1992; Orlikowski & Yates, 2002). Extant frameworks for multilevel theory (Chen et al., 2004; Chen et al., 2005; Kozlowski & Klein, 2000) and measurement (Bliese et al., 2007; Chan, 1998) also provide a point of departure.

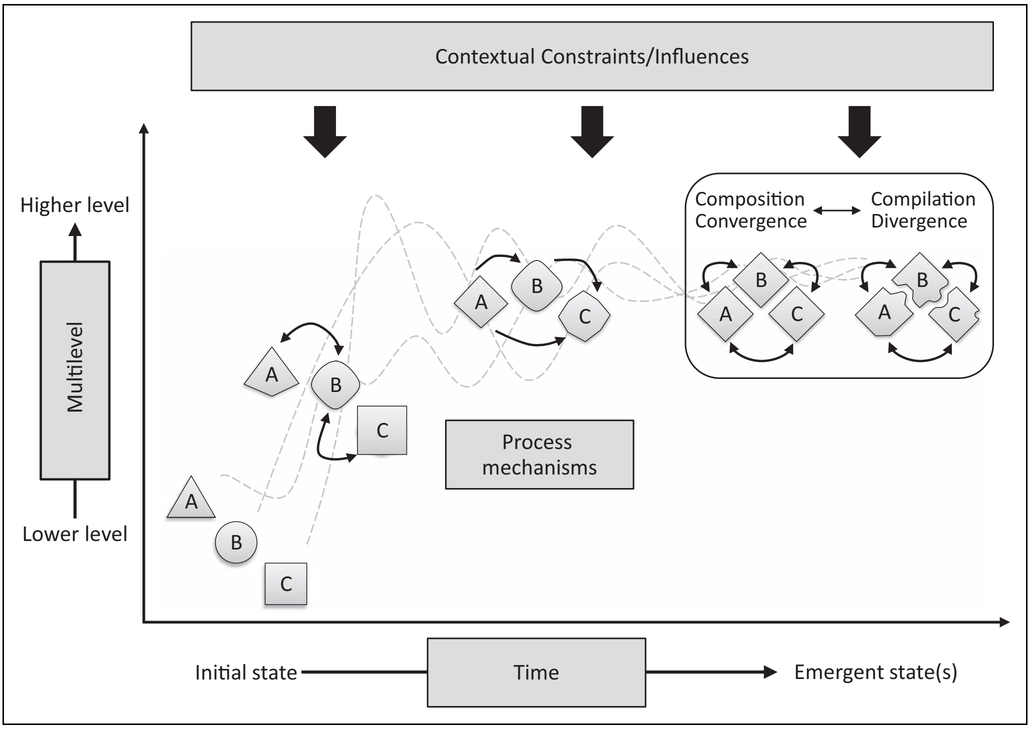

Figure 1. Heuristic illustrating core conceptual foci of emergence.

For example, the *typology of emergence* (Kozlowski & Klein, 2000) is consistent with our core conceptual foci and specifically describes different processes of interaction and exchange that yield different emergent forms, ranging from composition (i.e., convergent forms) to compilation (i.e., divergent forms). Thus, it provides a useful conceptual foundation for theory building. However, the fundamental process mechanisms relevant to specific substantive phenomena would typically have to be elaborated in more precise detail. This is particularly true for the nonlinear, compilation forms of emergence.

Second, emergence takes time to unfold and manifest. That means using longitudinal research designs and, to truly capture complexity in emergence, intensive longitudinal designs with many repeated measurements; not 5 or 10 or 20, but 30 or more (DeShon, 2012; Walls & Schafer, 2006). Sampling frequency should be dictated by the theory and research about the anticipated rate of change in the process mechanisms. This sets some obvious limitations on a heavy reliance on questionnaires as the primary source for the underlying data (e.g., intrusiveness, fatigue, response biases, construct drift, etc.). Moreover, for any particular research focus, the time scales relevant to how the phenomenon unfolds are critical to research design and measurement. This is particularly the case if the interaction processes are compressed into relatively short time frames. It is also the case that the process mechanisms of emergence are not likely to be captured well by modeling mean linear change trajectories over time (i.e., emergence as growth; Corning, 2002). That is merely one simple form. The more important focus of emergence is on process mechanisms and dynamics: *how lower level characteristics coalesce or diverge to create meaningful higher level patterns*.

Third, examining emergence for team processes is best conducted when a team or social unit first springs into being (Kozlowski & Klein, 2000). In existing social units with a history, emergence has already happened for most major phenomena. As Epstein (1999) notes, “If you didn’t grow it, you

	Indirect Investigation of Emergence [Retrospective; Emergence Inferred]	Direct Investigation of Emergence [Prospective; Emergence Observed]
Qualitative Methods [Interpretive]	**Quadrant 1** Retrospective Interviews; Case Studies • Orlikowski (2002) –five everyday practices of organizational members affect the emergence of "organizational knowing" • Robertson & Swan (2003) – the emergence of a strong organizational culture arise from ambiguous organizational practices that promote autonomy • Corley & Gioia (2004) – the emergence of an organizational identity change following a corporate spin-off	**Quadrant 2** Ethnography; Participant Observation; Action Research • Roy (1958) – emergence of a group's social structure is reinforced or changed by informal interactions • Kuhn & Corman(2003) – emergence of knowledge structures during an organizational change • Barrett, Oborn, Orlikowski, & Yates (2012) – changes in boundary relations among 3 occupational groups emerged over time as new technology was implemented
Quantitative Methods [Data Analytic]	**Quadrant 3** Multilevel Emergent Constructs / Relations • Lewis (2003) – questionnaire measure of transactive memory (TM) exhibited high within-group agreement; aggregated TM measure related to expertise agreement, functional communications, and team performance (Field Study 3) • Marks, Zaccaro, & Mathieu (2000) – leader briefings and team-interaction training predicted team mental model structural similarity and accuracy, which positively influenced team communication and performance (Experiment) • Sampson (2003) – aggregate social characteristics in communities are associated with individual health problems beyond individual risk factors	**Quadrant 4** Computation Modeling / Agent-Based Simulation • Dionne, Sayama, Hao, & Bush (2010) – leadership effects on the emergence of team mental models • Helbing, Yu, & Rauhut (2011) – social learning and social environmental effects on the emergence of cooperative behavior • Kuljanin (2012) – team interaction patterns and individual preferences for teamwork have effects on the emergence of team collaboration, which has effects on team performance

Figure 2. A metatheoretical framework for the empirical investigation of emergence in organizational science.

didn't explain its emergence" (p. 42). That means researchers have to capture teams at pre-formation (to assess any relevant individual differences), characterize the context (if possible), and then assess the development of the team long enough to capture emergence of the phenomena of interest. This is difficult to accomplish to say the least, which is perhaps why there is so little quantitative research on team development, let alone on emergence. Finally, all the typical concerns regarding sufficient sample size within and across teams and sufficient variability on all relevant substantive factors are still relevant. In our view, these challenges will be difficult to resolve with a sole reliance on conventional laboratory and field research designs using questionnaires that dominate organizational research.

Research Design Approaches

As illustrated in Figure 2, Kozlowski and Chao (2012a) described how empirical treatments of emergence in organizational research can be classified into four quadrants of a two by two matrix, structured by (a) the methodology used (qualitative or quantitative) and (b) the form of investigation (indirect or direct). With respect to qualitative research, Quadrant 1, *qualitative indirect*, is characterized by research using retrospective accounts (e.g., interviews, case studies, etc.) that attempt to capture interpretations of emergence after it has occurred. Emergence is an *inference*; the process is not captured directly. Quadrant 2, *qualitative direct*, is characterized by research that situates the observer in the midst of the people and system undergoing change (e.g., ethnography, participant observation, participatory action). With sufficient exposure across time, emergence as a process is captured directly in the observer's constructive interpretation and rich description. Kozlowski and Chao noted that the vast majority of direct empirical research on emergence in organizational science is qualitative. This research foundation offers theoretically rich accounts about potential process mechanisms undergirding emergence. Examining such processes with an eye toward precision, verification, and replication necessitates advances in quantitative research design.

Our focus is on advancing quantitative research, where treatments of emergence have been limited. Quadrant 3, *quantitative indirect*, is represented by contemporary micro–meso multilevel research that focuses on emerged constructs. This approach assumes a model of the emergence process (i.e., there is a theoretical rationale for how the phenomenon at the lower level combines to manifest at the higher level), but does not assess it directly. The emergence process is not the research focus, the emerged construct is. Emergence is an inference. Quadrant 4, *quantitative direct*, is largely characterized by simulation research using computational modeling in an effort to model the system dynamics of emergence. This approach treats the process of emergence as the central phenomenon of interest. Representing mechanisms that drive the process of emergence formally (i.e., mathematically) is the focal concern. The quantitative indirect and direct approaches employ distinct research designs and methods and, thus there has been very little cross fertilization. Yet, they have countervailing strengths and weaknesses. There is a potential for integration that can yield a hybrid research design with compelling theoretical and methodological advantages. We briefly describe each approach, identify strengths and limitations, and highlight how integration would enhance theory building and research design for the study of multilevel emergence.

Quantitative Indirect Approach. Contemporary cross-level and multilevel modeling in organizational behavior largely takes an indirect approach to emergence. Such research examines cross-level or multilevel models that incorporate combinations of direct, mediating, and/or moderating effects (Aguinis, Boyd, Pierce & Short, 2011; Kozlowski & Klein, 2000). Emergence is relevant in such models when a phenomenon originates at a lower level in the system (e.g., individual cognition, motivation/affect, behavior), but emerges theoretically as a higher level construct (e.g., team mental models, team collaboration). In this treatment, conceptualization of the process of emergence is important for guiding the level of measurement (i.e., at what level the construct should be measured and item referent specification), representation (i.e., how the data are aggregated or represented at the higher level [e.g., mean, variance, proportion]), and level of theory and analysis (i.e., level for model testing, inference, and generalization). However, the process of emergence is not examined.

Construct/measurement frameworks provide guidance to help researchers appropriately measure the phenomenon at the lower level and substantiate its representation at the higher level of analysis. Bliese et al. (2007) describe the conceptual challenges of aggregating lower level data to the higher level. Aggregation either maintains the lower level meaning or can yield a substantively different construct at the higher level; this problem is not trivial (Bliese, 2000; Chen et al., 2004; Chen et al., 2005; Sampson, 2003). Chan (1998), for example, distinguished five types of composition models (i.e., additive, direct consensus, referent shift, dispersion, and process). Although there are important conceptual differences, most types rely on the unit mean (i.e., additive, direct consensus, referent shift) for representing the higher level construct.[4] Dispersion models treat within-group variance as a meaningful focal construct, instead of error variance (Bliese & Halverson, 1998; Brown, Kozlowski, & Hattrup, 1996). Process models focus on how a process at a lower level might be conceptualized at a higher level (e.g., Kozlowski, Gully, Nason, & Smith, 1999). Chan offers no algorithm for representation and suggests more conceptual development of this model is needed to address the dynamics of change. Process models are essentially about emergence.

Kozlowski and Klein (2000) developed a typology to characterize emergence conceptualizations ranging between ideal types of composition emergence and compilation emergence. Their typology encompasses the same range of types as Chan's, but more theoretical attention is devoted to explicating the process mechanisms of emergence and making the different mechanisms explicit in the typology. It is the nonlinear compilation forms that characterize the most interesting—and least studied—types for investigation. These and other frameworks (Bliese, 2000; Chen et al., 2004; Chen et al., 2005) are used to provide a theoretical basis for (a) specifying *assumptions* about the emergence process for a construct and (b) drawing emergence *inferences* to provide construct validity for the aggregated representation.

Key strengths of this approach are the construct validity it extends to emergent constructs and, thus, inferences drawn about their meaning and generalization at higher levels. This is by no means trivial. It took a quarter century of theory, research, and discourse to develop the conceptualization, methods, results, and scholarly consensus to support the validity of emerged/aggregated constructs. Considering the research challenges highlighted previously, one could use a longitudinal field research design to track the emergence of team processes using this approach. For example, with appropriate sampling one could track the degree of within-group agreement on constructs of interest and model their convergence, divergence, and variance over time using LGM (Kozlowski, 2012). A similar design could be employed with a laboratory simulation, assuming that the phenomenon emerges quickly.

Nonetheless, the approach also has some inherent limitations. First, by virtue of the primary use of questionnaires for measurement in both field and lab research, the assessment is typically self-reported and retrospective over some time frame. Even if the investigator is interested in the emergence process per se, this method of measurement tends to miss the fundamental mechanisms underlying the process. Second, the assessment is typically static. It need not be so, but the primary purpose of this approach (i.e., to populate a model with measures of stable constructs) generally yields a single assessment of the construct in question. The measurement periods could be spaced over time to help reduce causal ambiguity among constructs (Collins & Graham, 2002), but that is not common practice. Cross-sectional designs predominate in field research (e.g., Austin, Scherbaum, & Mahlman, 2002), and lab research is more sensitive to temporal ordering than it is to emergence as a process (e.g., Kozlowski, 2012). Third, emergence as a process is assumed within this approach and is typically treated as universal for all units. We know from the limited research that treats within-group agreement as a substantive construct of interest rather than a mere statistical criterion for aggregation (Brown et al., 1996) that this assumption is tenuous at best (Gonsalez-Roma, Peiro, & Tordera, 2002; Schneider, Salvaggio, & Subirats, 2002).

Quantitative Direct Approach. Most quantitative research in the social sciences relevant to emergence as a process of direct interest has utilized computational models and agent-based simulation as the primary research design approach (Epstein, 1999; Miller & Page, 2007). A computational model provides a mathematical depiction of a phenomenon of interest representing the mechanisms by which a dynamic process unfolds (Busemeyer & Townsend, 1993; Hulin & Ilgen, 2000; Miller & Page, 2007). It is focused on the *theoretical mechanisms* of emergence as a process. Such models specify mathematical equations or logical if–then statements to specify system dynamics from one time point to the next (Harrison, Lin, Carroll, & Carley, 2007; Vancouver, Tamanini, & Yoder, 2010; Vancouver, Weinhardt, & Schmidt, 2010). Thus, the computational model formally specifies a set of rules or goals that guide the behavior of entities or "agents" of interest, *in dynamic interaction with other entities*. Typically, the behavioral rules are theoretically driven (although atheoretical descriptive models are possible). An agent-based simulation instantiates the computational model in programming code, arranges the agents at Time 0 into an environment, and executes dynamic interactions among the agents following the rules within the constraints of the environment. Collective, system-level phenomena emerge as the simulation runs and individual agents interact dynamically over time.

The computational, agent-based simulation of bird flocking by Reynolds (1987) is a good illustration of how a concise set of basic process mechanisms can emulate complex, system-level behavior that emerges from the dynamic interactions of individual agents—boids. The agents optimize three basic rules: (a) the separation rule directs boids to move away from other agents to minimize collisions, (b) the alignment rule directs boids to move in the average direction of other agents, and (c) the cohesion rule directs boids to move to the center of the cluster. Boids are randomly placed in a computational space, and the simulation runs. As the code for each boid maximizes its rule set—in dynamic interaction with the other boids—collective flocking emerges. Flake (1998) proposed the addition of a fourth view rule—move to avoid boids blocking the view—that then yields the V formation of a migrating flock. This computational simulation is an excellent example of how complex group behavior emerges dynamically from individuals striving to maximize a parsimonious set of goals or rules as they interact with other goal-striving individuals, within the constraints of the environment.

A key issue for the effective use of computational, agent-based modeling as a research design approach pertains to drawing meaningful inferences about the correspondence of the process rules inherent in the computational model and the natural phenomenon of interest. As noted by Epstein (1999), "Agent-based models provide computational demonstrations that a given micro specification is in fact sufficient to demonstrate a macrostructure of interest" (p. 42). This concept of "generative sufficiency" is consistent with concepts of, and evidence for, construct validity. It is important to note, however, that mere fidelity is necessary but not sufficient to demonstrate that a given set of micro behavior specifications (i.e., rules) account for the observed behavior in the natural system. Real birds, for example, do not necessarily strive to maximize the four boid rules. Fidelity makes those rules appropriate candidates for explanation, but other competing rules need to be considered and evaluated. Theory provides a guide, and, importantly, more direct correspondence and verification with real-world data and experimentation are necessary (Epstein, 1999).

Computational models and agent-based simulations have several key advantages as a direct research design approach for emergent phenomena in teams, especially considering the research challenges highlighted previously. For example, the computational model necessitates a formal specification of the theoretical mechanisms (i.e., precision), and the idea is to model the system with as few rules as necessary (i.e., parsimony) to simulate the emergent phenomenon in question. Time periods and sampling frequencies are restricted only by computing power. Teams are easily formed anew and tracked across a hypothetical life cycle. And any number of teams with variability on any number of characteristics can be examined in any number of environmental contexts, again constrained only by computing power. This enables virtual experimentation in a model space that can fully encompass variance across all theoretically relevant factors. This is a major advantage relative to more conventional research designs.

These are significant strengths for the study of emergence, but there are important limitations that have to be acknowledged. Theoretical complexity is one. Human behavior is complex and multiply determined, but computational simulations (at least in the beginning of a research program) are better when sparse. The many specific theories of team functioning or organizational behavior are primarily "word" based using natural language descriptions, rather than clearly specifiable process mechanisms. Thus, computational modeling will often necessitate theory building to specify process mechanisms with precision, perhaps not a bad thing for advancing organizational science. Moreover, once mechanisms are specified in a computational model, parameter values to operationalize the mechanisms need to be extracted from the literature so agent behavior is calibrated realistically. This is not as straightforward as one might expect, and initial model parameters can be imprecise. However, as we describe later, coupling computational modeling with conventional research designs provides a means to coevolve the specification of model mechanisms and parameter values. Finally, validating a computational model necessitates real data so the veracity of the model and its parameters can be established. Relevant data may not exist, may be difficult to acquire, or may lack the necessary granularity to provide good assessments of model fidelity and fit (Hulin & Ilgen, 2000). This means that one has to be thoughtful about the phenomenon one chooses to model.

Given its potential to model complex, dynamic, emergent system behavior, computational modeling has substantial potential as a research design approach for studying emergence in organizational science, particularly those aspects that are very challenging with traditional laboratory or field observations. However, there has been only very limited attention to applying this approach. Most applications have been macro oriented (Harrison et al., 2007), although there have been some with a more psychological focus on withdrawal (Hanisch, Hulin, & Seitz, 1996) and motivational processes (Vancouver, Tamanini, et al., 2010; Vancouver, Weinhardt, et al., 2010). "Modeling is the 'redheaded stepchild' of organizational research methods; it is useful for a number of issues important to behavior in organizations, but it has been little used and is little appreciated" (Hulin & Ilgen, 2000, p. 7).

An Integration. We think it is evident that indirect and direct approaches to studying emergence quantitatively have countervailing strengths and weaknesses. We assert that a thoughtful integration of these distinctive methodologies can enable quantitative researchers to begin probing the processes of multilevel emergence. Field-based correlational designs (i.e., nonexperimental) and laboratory-based experimental designs have offsetting strengths and weaknesses. Field research is typically viewed as stronger on generalization and weaker on causal inference relative to lab research. Researchers are well schooled in these trade-offs. Good research to understand a problem domain has to utilize both designs to ensure solid inference and good generalization. Hulin and Ilgen (2000) characterize computational modeling as a "third discipline" commensurate with Cronbach's (1957) characterization of correlational and experimental designs as the two primary research disciplines of scientific psychology. Just as correlational and experimental research have offsetting strengths and limitations, so does computational modeling as a third discipline relative to the other two. We are not advocating that computational modeling be used instead of conventional quantitative research. Rather, we are advocating that organizational science embrace computational modeling as an additional research methodology that has distinct advantages for studying the dynamic processes that undergird emergence. As we explicate in the next section, computational modeling has an important and valuable role to play as a methodology for conducting virtual experimentation and building theory. Modeling enables discovery. Tried-and-true conventional quantitative methods are still essential for estimating parameter values for mechanisms, testing predictions from virtual research, and verifying model findings.

Advancing Multilevel Research on Emergent Phenomena

Exemplars: Emergent Team Processes and States

Criteria. It is useful to reemphasize the core foci for conceptualizing multilevel emergent phenomena from our definition (see Figure 1). First, emergent phenomena are *multilevel*, transcending their level of origin. They originate at a lower level and emerge as a collective macrostructure at a higher level (Crutchfield, 1994; Epstein, 1999; Kozlowski & Klein, 2000). Second, they are *process oriented*, with emphasis on the dynamic interactive *process mechanisms* that drive the nature of, and forms of, emergence from the lower to the higher level (Kozlowski et al., 1999). Third, they are *temporally sensitive*. Manifestation of the collective property takes time, entailing developmental and episodic changes (Bedwell et al., 2012; Marks, Mathieu, & Zaccaro, 2001).

Exemplars. The meso level, at the intersection of the micro and macro, provides a rich slice of organizational life within which a multitude of emergent phenomena exist. Most "team processes" are not researched as emergent phenomena, although they are certainly conceptualized as emergent because they incorporate the core conceptual foci. Thus, they provide theoretically appropriate and

Table 1. Exemplar Emergent Phenomena in Teams.

Emergent Team Processes and States
Cognitive perceptions and states
• Team or unit climate (Zohar & Hofmann, 2012)
• Team learning and knowledge acquisition (B. S. Bell, Kozlowski, & Blawath, 2012)
• Team knowledge outcomes
○ Shared team mental models; transactive memory (DeChurch & Mesmer-Magnus, 2010a)
Motivational and affective perceptions and states
• Team goals (Kleingeld, van Mierlo, & Arends, 2011)
• Team efficacy and potency (Gully, Incalcaterra, Joshi, & Beaubien, 2002)
• Team cohesion (Gully, Devine, & Whitney, 1995)
• Team conflict (De Dreu & Weingart, 2003; de Wit, Greer, & Jehn, 2012)
Group decision making
• Social dilemmas (Dawes, 1980; Kollock, 1998)
• Hidden profiles (Stasser, 1999; Stasser & Titus, 1985)
• Social decision scheme (J. H. Davis, 1996)
Behavior and action
• Collaboration and interaction (Bedwell et al., 2012)
• Action and transition (LePine et al., 2008; Marks et al., 2001)
• Action regulation (DeShon et al., 2004)

practically relevant targets for theory building and research program development aimed at unpacking the nature of emergence in organizational behavior. We have synthesized across reviews and taxonomies to identify a range of exemplar emergent phenomena in teams ripe for research and investigation. The listing shown in Table 1 is not intended to be comprehensive—we have not tried to list all emergent phenomena—but instead to illustrate the wide array of phenomena for which a research focus on emergence is relevant. These are potential targets for new research.

Fundamental Research Questions. Multilevel research does not examine the emergence of these phenomena directly, although it does examine whether aggregating individual perceptions or behaviors into a higher level construct is justified. Thus, there are several fundamental research questions that are relevant for each of these phenomena, as well as for others we did not list, that are currently unexplored in the literature. This represents a substantial gap in organizational science. Addressing these fundamental questions is relevant to advance theory *and* to develop interventions and tools to shape emergence processes.

- What are the primary *micro process mechanisms* that account for emergence for the phenomenon of interest?
  - What parsimonious "rules" drive human interaction and exchange such that a collective macrostructure manifests (Epstein, 1999)?
- How do *patterns of emergence evolve* for the phenomenon of interest?
  - What forms do they assume? Composition via convergent forms? Compilation via divergent forms? Complex patterns that may involve both convergent *and* divergent processes (Kozlowski & Klein, 2000)?
- What are the primary antecedents that shape the nature of the emergence process?
  - What individual characteristics and contextual (environmental) constraints shape the process, pattern, and outcomes of emergence?
- What kinds of shocks shape or change the nature of the emergence process?
  - Shifts in the context may fundamentally alter patterns of composition or compilation emergence.

In the next section, we examine limitations inherent in the indirect research designs applied to select exemplars in Table 1 and highlight the benefits of incorporating direct designs that use computational modeling. We sampled across the categories to showcase the generality of a focus on emergence and modeling. We selected team mental models from the cognitive category,[5] social dilemmas from the group decision category, and collaboration from the behavior category. For each exemplar, we describe the conceptualization of the phenomenon, the general treatment in mainstream research, and the usual research design used to study the phenomenon. We then highlight fundamental research questions that are not addressed or not addressed well, and illustrate how computational modeling and agent-based simulation can be used to illuminate the phenomenon, promote theory building, and enhance understanding.

Team Process Perceptions: Team Cognition

Conceptualization. Shared team mental models (STMM) and transactive memory (TM) are commonly studied team cognition perceptions. STMMs represent the "knowledge structures held by members of a team that enable them to form accurate explanations and expectations for the task, and in turn, to coordinate their actions and adapt their behavior to demands of the task and other team members" (Cannon-Bowers, Salas, & Converse, 1993, p. 228). In contrast to this shared conceptualization, TM is a team-level system distributed across team members for encoding, storing, and retrieving team knowledge (Wegner, 1995; Wegner, Giuliano, & Hertel, 1985). STMMs are viewed as having emerged via composition emergence, whereas TMs are conceptualized as emerging via compilation processes.

Both STMM and TM are viewed as emergent states that reciprocally shape, and are shaped by, interactions among team members (Marks et al., 2001). Conceptually, they are created through an emergence process that begins at the individual level and, through repeated interactions, manifests at the team level. The predominant focus of research on these team cognitive constructs is consistent with the input-process-output (I-P-O) model of team effectiveness (McGrath, 1964) or its more recent variants (Ilgen, Hollenbeck, Johnson, & Jundt, 2005; Kozlowski & Ilgen, 2006). It is treated as a mediator that links a variety of antecedents such as team composition (Edwards, Day, Arthur, & Bell, 2006), team communication (K. Lewis, 2004; Marks, Zaccaro, & Mathieu, 2000), team coordination (Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000), leadership (DeChurch & Marks, 2006), and training (Liang, Moreland, & Argote, 1995; Marks, Sabella, Burke, & Zaccaro, 2002) to team effectiveness outcomes such as team performance and viability (DeChurch & Mesmer-Magnus, 2010a, 2010b; K. Lewis, 2004).

Research Treatment. Given the primary research focus on team cognition as a mediator, almost all studies have measured STMMs and TM through the use of indirect quantitative methods. There are two primary ways in which STMMs are typically measured and operationalized (DeChurch & Mesmer-Magnus, 2010b). If the focus is on the congruence of *knowledge content*, then questionnaires are administered to all members of the team and their responses are aggregated to form a collective construct. Prior to aggregation, a team agreement index such as r_{wg} or a team interrater reliability index such as the intraclass correlation coefficient (ICC(1)) is used to verify that there is sufficient restricted within-group variance among members, indicating that the construct has emerged at the team level. Alternatively, if the focus is on the congruence of *knowledge structures*, then each team member completes a card-sort task or Pathfinder to create a structural representation of team knowledge. Congruence across members is computed by taking the Euclidian distance between the structures of the team members. Much like STMM knowledge content, TM is typically measured using a scale developed by K. Lewis (2003) to assess the degree of within-group consensus on perceptions of the distributed knowledge structure of the team. This approach measures each individual's understanding of the team's TM and then aggregates each individual's responses to the team level if sufficient agreement (using ICC(1) or r_{wg}) is achieved.

Researching Emergence. Informative relationships among antecedents, emerged STMM and TM constructs, and team effectiveness have been examined using this methodology. Yet, a key limitation with the use of ICC(1), r_{wg}, and Euclidian distance as indicators of STMM and TM emergence is that sufficient team member agreement must be reached for the measure to be aggregated as a team-level construct, implying that emergence is complete. The assessment is retrospective and emergence is an inference based on the indicators of restricted within-group variance on the construct measure. There is no direct observation of emergence as a process.

There is also a gap between the conceptualization and measurement of TM. STMMs as shared knowledge among team members represent a compositional emergent state. In contrast, the conceptualization of TM is based on a distribution or pattern of knowledge held across team members, a compilational emergent state. The commonly utilized methodology to study TM does not capture the compilational nature of the construct conceptualization. As a result, the uniqueness of TM as a compilation construct, above and beyond STMMs, has not been examined (Kozlowski & Ilgen, 2006).

These are substantial gaps in the team cognition knowledge base that are largely due to measurement and research design limitations inherent in an indirect assessment of STMM and TM emergence. However, the emergence of STMMs and TM can be studied directly through the use of computational simulation. This would allow researchers to supplement current approaches—that examine I-P-O relations among antecedents, STMMs, TMs, and team outcome constructs—with theoretically driven quantitative investigations into the process mechanisms of emergence that undergird the formation of these relationships. Combining a fine-grained theory with the use of computational simulations would allow researchers to explore directly how antecedents influence the emergence of team cognition, variation in the ways in which emergence unfolds, and how process variations influence relevant outcomes. For example, research on STMM emergence has mathematically specified theoretically driven behavioral cues that contribute to team cognition (McComb, 2007), as well as to estimate how different leadership styles interact with task properties to alter the formation of STMMs and affect team performance (e.g., Dionne, Sayama, Hao, & Bush, 2010). Similarly, researchers have attempted to test how different patterns of STMM emergence can lead to different team decision-making strategies (Sayama, Farrell, & Dionne, 2011). Sayama et al. (2011) identified one particular pattern of STMM emergence that led teams to focus on only a small amount of task-relevant information. This finding provides one possible explanation for the common finding that teams tend to focus primarily on sharing common information and ignore unique information, which yields biased decisions (Stasser, 1992).

The examples demonstrate how computational modeling can be used to systematically examine process mechanisms thought to drive construct emergence. Despite the potential of this approach, such research has barely tapped its potential. Many important questions as to how STMMs and TM emerge over time are unaddressed. Of particular importance is advancing understanding of how STMM composition and TM compilation processes influence one another over time. In current research, these forms of shared cognition are largely studied independently (DeChurch & Mesmer-Magnus, 2010a). Yet, both forms of team cognition are theoretically relevant. For example, it is conceivable that in some teams (i.e., with distributed expertise), knowledge begins initially as widely distributed across members; consequently, the manner by which the TM system emerges within the team (i.e., how individuals learn who knows what on the team, the mechanisms by which members store and extract information from others) is fundamental. Over time, however, as team members share their unique distributed information (e.g., Fiore et al., 2010), team knowledge may converge to a common cognitive representation; a shared mental model. Thus, in this example, team knowledge evolves from a patterned compilation form of emergence to a converged composition form (Kozlowski & Chao, 2012b). Conversely, for other teams, members may initially have identical information, such that the emergence of an STMM has priority. Over time, however, as each team member searches for new information or has unique experiences, distributed expertise develops. Team knowledge evolves from a shared composition form of emergence to a configural compilation form.

Another research target could examine how STMMs and TM systems change as new information is discovered. As teams accumulate experience, encounter novel situations, and work collaboratively to complete their tasks, members may need to integrate new information (e.g., a new task protocol requires that members incorporate a new information source). The way that new information sources are embedded within and reshape the knowledge structures of individual members should subsequently influence the quality and effectiveness of STMMs and TM systems. Although this issue has not been pursued at the team level, research investigating the growth of individual semantic networks offers a potential point of departure. Specifically, researchers have developed computational simulations that plausibly model the process by which newly learned words are incorporated into a person's semantic network based on the characteristics and interrelations among existing words in memory (Steyvers & Tenenbaum, 2005). Such a model could be adapted to explore how STMMs and TM systems react to and absorb the "shock" of members learning to make use of novel information.

For cases such as these, directly investigating the emergence of STMMs and TM through the use of computational simulation can be valuable for theoretical insights. Given a theoretical specification of the emergence process, it is possible to manipulate different initial knowledge distributions, task demands, team durations, and other antecedents and moderating factors of interest to determine how they affect teams' STMM and TM emergence. Relevant research foci include investigation of factors that shape the form of emergence (composition or compilation), influence the rate of emergence, or affect the stability of the emerged form (e.g., Kozlowski & Chao, 2012b; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2012). In addition, it is also possible to examine how STMMs and TMs interact over time, or evolve along different tracks, to make teams differentially effective at adapting to task characteristics. Determining such relationships with conventional experimental or correlational research designs would be very challenging, which is likely why these conceptual issues have not yet been pursued empirically. The use of computational simulation to supplement conventional designs can therefore provide researchers with unique insights for theory building and for better targeting the focus of conventional research designs.

Group Decision Making: Social Dilemmas

Conceptualization. Social dilemmas are problems that oppose immediate individual gains against long-term collective interests (Dawes, 1980; Oskamp, 1971). This research area is a good exemplar because more than 50 years of traditional quantitative research and 30 years of computational modeling have yielded a large body of knowledge that, together, advances theoretical understanding of how and why cooperative decision making emerges in a group. Dilemmas between individual gains and collective losses can lead to catastrophic societal problems if the combined behaviors of too many self-serving individuals result in egregious depletion of natural resources, pollution, or overpopulation (Dawes, 1980). Core research examines how cooperative behavior emerges within groups to preserve collective interests.

Research Treatment. Research on social dilemmas generally involves mixed-motive games with explicit payoffs, requiring individuals to either cooperate (C) with one another for a modest payoff or defect (D) from such cooperation and thereby win a bigger payoff from a selfish advantage. A common example is the Prisoner's Dilemma (PD) game (Axelrod, 1980a, 1980b; Luce & Raiffa, 1957), where two players generate four possible payoffs that are rank ordered DC > CC > DD > CD for the first player (i.e., first letter in the two-letter decision outcome). Game rules generally embody two properties of social dilemmas: (a) The payoff for defecting is higher than the payoff for cooperating, regardless of what others do, and (b) if all individuals cooperate, the payoff is higher than if all individuals defect (Dawes, 1980). Iterated PD games examine decision-making strategies that emerge as a history of interactions unfolds.

A computer search of peer-reviewed published articles on social dilemmas yielded more than 3,500 hits. Researchers from several disciplines contribute to this literature, using a variety of social dilemma contexts and research designs (Gotts, Polhill, & Law, 2003). Within psychology, much of the empirical research involves laboratory experiments, with few field studies (e.g., Joireman et al., 2001). Individual differences are generally treated as antecedents for cooperative behavior and include studies on social value orientation (Balliet, Parks, & Joireman, 2009), mood (Hertel, 1999), trust (Foddy & Dawes, 2008), individualism/collectivism (Boles, Le, & Nguyen, 2010), and gender (Walters, Stuhlmacher, & Meyer, 1998). Experimental manipulations of the social dilemma context are designed to compare different rates of cooperation. Game conditions such as small group sizes, external authorities who can regulate player behavior, and sanctions against defectors have all been found to promote cooperation (Dawes, 1980; Kollock, 1998). Other research has varied game conditions related to communication (Orbell, van de Kragt, & Dawes, 1988; Samuelson & Watrous-Rodriguez, 2010), feedback (van Dijk, De Cremer, Mulder, & Stouten, 2008), rewards and punishments (Balliet, Mulder, & van Lange, 2011), and uncertainty (Kramer, 2010). Despite this large body of research, and common usage of longitudinal designs, the emergence of cooperation in group decision making is not directly examined. Rather, it is inferred from cooperation rates, measures of common resources used, or contributions to other players.

Researching Emergence. Remarkably, despite the 1,000-plus experiments with the PD metaphor for social dilemmas (Dawes, 1980), there has been no systematic effort to identify the process by which cooperation emerges. Research includes many one-shot PD studies that were not designed to examine how decision making strategies unfold and adapt to a history of exchanges. Furthermore, results from iterated PD studies are generally aggregated across trials to examine rates of cooperation at the end of the study, instead of examining how those rates evolve over time. Experiments provide valuable insights on who is predisposed toward cooperative decision making and what conditions might facilitate cooperation, but they have practical constraints related to sample sizes, number of conditions, and capturing a process within one game play. Thus, understanding the multilevel, process-oriented, and time-dependent foci of emergence is challenged with these research methods.

In contrast, computer simulations are not constrained in ways that limit experimentation. For example, Fischer (2003) ran 30 replications of simulations that crossed 8 rates of iterations per interaction with 4 initial distributions of decision making strategies, for a total of 960 simulations. Furthermore, each simulation ran with 300 agents, the number of iterations per interaction ranged from 1 to 10,000, and an entire simulation ran for 200,000 iterations of interactions between two agents. These simulations provided evidence that the emergence of cooperative strategies was highly influenced by the duration of social influence (iterations per interaction). Smithson and Foddy (1999) argued that simulations offered more control than empirical research because the range of relevant conditions can be thoroughly and systematically examined with large numbers of agents that can be reset for reruns.

Computer simulations often examined multiple agents playing PD games in a two-dimensional space (Axelrod, 1997; Nowak & May, 1992). These simulations provide a more realistic and dynamic decision-making context where agents are not equally likely to play with all other agents. Agents play only with their neighbors, they can learn strategies from better players, and they can move about, seeking new neighbors to play subsequent games. For example, Helbing, Yu, and Rauhut (2011) examined two strategies for iterated PD simulations in their game environment. First, social learning was modeled by having an agent adopt the strategy of its most successful neighbor. Second, agents could move to unoccupied spaces, searching for new players that might prove to be more successful for the agent. Computer simulations of each strategy alone resulted in low levels of cooperation. However, when the two strategies were combined, individual behavior and social environments coevolved, resulting in the emergence of cooperative clusters. Cooperating agents clustered together, forming a tight community that maintained cooperation. In contrast, defectors were relegated to the boundaries of these cooperating neighborhoods, unable to penetrate inside the cluster. Such findings are insightful for theory building. Other simulations with spatial PD games have examined the importance of sufficient learning intervals to the emergence and sustainability of cooperation (Fischer, 2003), the emergence of role differentiation (leaders) in self-organized clusters (Eguíluz, Zimmermann, Cela-Conde, & San Miguel, 2005), and the moderating effect of heterogeneity of degree (variance in social network ties) on the emergence of cooperation (Jones, 2008; Roca, Sánchez, & Cuesta, 2012).

Although we did not find any research that directly integrated quantitative empirical research and simulation methods, researchers from each perspective are clearly aware of both bodies of work (Liebrand & Messick, 1996). For example, Kollock (1993) ran computer simulations, looking at noise effects on different decision making strategies. He found that the detrimental effects of noise could be ameliorated by more generous or cooperative decision making. Van Lange, Ouwerkerk, and Tazelaar (2002) supported Kollock's findings in their lab experiments. This research provides a good example of how human experiments and computer simulations are complementary and advance understanding of how people negotiate competing individual and group interests. Empirical research probes the complexity of social dilemmas and computer simulations provide systematic tests of many proposed solutions. Results from these two research methods stimulate new research streams within and across these methods.

Van Lange, Joireman, Parks, and van Dijk (2013) reviewed traditional empirical research on social dilemmas and noted that most variables were static in nature, unable to capture how a decision maker learns from others and actively responds in subsequent decisions over time. They suggest future research can target five factors related to dynamic interaction processes: (a) reciprocal decision-making strategies, (b) reputation effects, (c) changes in group composition or players, (d) communication, and (e) structural solutions (e.g., selecting a leader). They note that the emergence of cooperation is more likely to result when a combination of these factors influence trust, generosity, and/or forgiveness among players. To illustrate one factor, reputation effects, Weber and Murnighan (2008) challenged the notion that consistent cooperators are suckers for exploitation by defectors. Their experimental results suggest that consistent cooperators had a positive effect on other players, subsequently encouraging cooperative behaviors from them. However, they admit that their data could not predict when a consistent cooperating strategy would emerge or what might stop or change this strategy. Simulations that examine how cooperative behaviors can self-organize and emerge as social units within a larger environment are likely to advance this area of group decision making.

Results from indirect (lab/field quantitative research) and direct (computational simulation) research methods should be integrated to advance understanding of social dilemmas; however, there remain significant challenges. Simulations by Roca et al. (2012) showed that the emergence of cooperation was extremely sensitive to micro-dynamic changes in spatial or social structures. Not all social networks support cooperative behavior, and results vary depending on the type of interaction (e.g., game) and information (e.g., updating strategy). Research can use counterintuitive findings from empirical research (e.g., generous cooperators are not always exploited by defectors) to inform new computational models to help predict when cooperation emerges and under what conditions it would change.

Behavior and Action: Collaboration

Conceptualization. In an attempt to distinguish it from related concepts such as coordination, cooperation, and teamwork, Bedwell et al. (2012) define collaboration as "an evolving process whereby two or more social entities actively and reciprocally engage in joint activities aimed at achieving at least one shared goal" (p. 130). Collaboration meets the core criteria of an emergent phenomenon: Its manifestation is at a higher level driven by the interactions of multiple constituent entities (multilevel; e.g., Graham & Barter, 1999; Longoria, 2005), it is characterized by dynamic exchanges that influence and are influenced by those constituent entities (process oriented; e.g., Gray, 1989; Keyton, Ford, & Smith, 2008; L. K. Lewis, 2006), and the procedural mechanisms and resultant states require time to develop (temporally sensitive; e.g., Tucker, 1991; Wood & Gray, 1991). As is true of all emergent phenomena, collaboration is also responsive to external, top-down environmental factors and task structures that shape or constrain workflows and other forms of interactive engagement (e.g., sequential task interdependence; Saavedra, Earley, & Van Dyne, 1993). Nevertheless, the underlying behavioral and psychological dynamics necessitate circumstances that permit discretion and autonomy (Steiner, 1972) to social entities as they perform tasks, thereby allowing them to engage in collaborative efforts to achieve shared goals (Bedwell et al., 2012).

Research Treatment. Within the broader research literature, examinations of team collaboration have been somewhat muddied by imprecise definitions and only implicit acknowledgment—but not direct examination—of its dynamic processes (Bedwell et al., 2012; Henneman, Lee, & Cohen, 1995). The general focus of mainstream research on collaboration has largely centered on antecedents (e.g., Salas, Sims, & Burke, 2005) and outcomes (e.g., Stout, Cannon-Bowers, Salas, & Milanovich, 1999) of the process or factors that purportedly shape individuals' collaborative interactions (e.g., Saavedra et al., 1993; Stout, Salas, & Fowlkes, 1997). Over the past decade, greater attention has also been directed toward capturing descriptive measures of team processes and examining relations between the frequency or quality of team behaviors indicative of collaboration and various indicators of team functioning and effectiveness (cf. LePine, Piccolo, Jackson, Mathieu, & Saul, 2008). Although varied depending on the research question of interest, the modal quantitative approaches applied to the study of team collaboration have most often been correlational, cross-sectional, or (more rarely) repeated measures designs using a small number of observations. To be sure, the aggregate findings from the current literature have significantly improved our understanding of the various factors that influence and result from a team's collaborative efforts. Nevertheless, these modal methodological approaches and research foci have not yet offered great insight into the fundamental research questions we have posed previously for the study of emergent phenomena. As a result, there is substantial value to be added to this research domain through investigation of the dynamic forms, mechanisms, and changes related to team members' interdependent exchanges that characterize team collaboration.

Researching Emergence. Like STMMs, transactional memory, and social dilemma exemplars, computational modeling techniques offer a number of advantages over current research designs for capturing emergence. For example, physicists have begun to develop computational models that directly investigate patterns of human interaction that may prove useful for understanding the emergence of collaboration (Barabási, 2005; Oliveira & Vazquez, 2009). One particularly useful model, proposed by Min, Goh, and Kim (2009), consists of a group of computational agents linked together via two different network topologies (i.e., star network vs. fully connected network) performing tasks with or without the help of a teammate under two sets of rules for interaction (i.e., both agents consent to work with each other vs. one agent obliges to work with its teammate only on request). Their results describe how these different network topologies and rules for agent interaction affect the frequency and pattern of group collaboration.

To further explore the process mechanisms driving collaborative group behavior and performance, Kuljanin (2011) built on this approach by including individual team member preferences for collaborative work and additional team network topologies. Individuals differ in the extent to which they wish to accomplish tasks with the assistance of teammates or on their own depending on goals, incentives, and feedback structures (Wagner, 1995). Meta-analyses indicate preferences for collaborative work is an important dispositional predictor of team performance (S. T. Bell, 2007). However, the impact of preferences for collaborative work may be amplified or attenuated depending on the interconnectivity of teammates, represented by a team's network topology, which then affects team effectiveness (Losada, 1999). Among the unique virtual experiments pursued in the computational modeling by Kuljanin (2011), one primary goal was to investigate how different collaborative systems contribute to effective (or ineffective) utilization of the unique skills team members possess. Simulated teammates worked on a collaborative project consisting of numerous tasks. Each agent performed tasks on its own or with help from a teammate; whether a teammate agent collaborated depended on the team's collaboration network, the rules for dyadic interaction, and agent preferences for collaboration. At a broad level, the results of this research revealed how different patterns of team interaction and individual differences can directly influence a team's collaborative efforts to yield performance outcomes. Additional theoretical work in this domain might consider how particular collaborative networks and different rules for interaction emerge, as well as how these mechanisms and structures adapt in response to changing tasks or environments.

Although work that links team collaboration computational models with human data in a singular research effort does not yet exist, such computational work fits nicely with recent empirical efforts by sports psychologists that employ dynamic network analyses to study collaboration among team members. Studying the complete set of interactions of a youth basketball team for one quarter of an international game, Bourbousson, Poizat, Saury, and Seve (2010) verified that a human team utilized similar team collaboration networks and rules for interaction as those studied by Min et al. (2009) and Kuljanin (2011). While Bourbousson et al. (2010) focused on describing the interactions that took place within the team, Passos et al. (2011) mapped the team collaboration network of two competing water polo teams and discussed implications for their team performance. In many respects, the results of these empirical pursuits largely coincide with the processes, collaborative networks, and performance outcomes modeled by Kuljanin (2011). Consequently, such studies represent exemplary demonstrations of the methodological approaches one could employ to empirically validate the predictions gleaned from computational models of team collaboration.

With respect to future research directions that explore emergent phenomena within this area, Bedwell et al. (2012) cite six key types of team member activity that characterize team collaboration: (a) adaptive behavior, (b) information processing, (c) sense making, (d) task execution behavior, (e) extrarole behavior, and (f) leadership behavior. Attempts to model the processes and mechanisms that explicate how team members enact, make use of, and structure interactions within each of these areas represent a rich and as yet untapped source of knowledge concerning how, when, and why reciprocal exchanges contribute to the emergence of team collaboration. As one possible point of departure, early research on punctuated equilibrium models of team development postulates that teams undergo sudden and dramatic shifts in their collaborative efforts as critical task deadlines approach (Gersick, 1988, 1989); that is, the fundamental processes underlying team collaboration purportedly change as a result of team members' recognition of the task environment's temporal pacing. What are the mechanisms that describe how and why teams suddenly shift their collaborative team behaviors? The punctuated equilibrium model considers time as an antecedent, but time is merely a trigger. What do team members perceive, and how does that translate into process mechanisms that change the dynamics and form of team member interaction? For example, might the various behaviors explicated by Bedwell et al. (2012) interact to produce different patterns of collaborative development? What is the manner by which these collaborative mechanisms manifest at different points in time (e.g., all team members exhibit slow change until a critical threshold is reached, some team members engage in new behavioral processes which stimulate others to follow suit, etc.)? In addition, contextual characteristics may shape emergence processes. How might different types of team configurations (e.g., leaderless teams, cross-functional teams, etc.) contribute to earlier or later manifestations of collaborative interaction? Such research questions hold significant implications for teasing apart the specific patterns and mechanisms of interdependent behaviors and actions directly relevant to team collaboration that can be evaluated only through the study of the phenomenon's emergence.

The area of team collaboration clearly marks a prime target for the use of virtual experimentation and computational modeling techniques to study the complexity of team collaboration dynamics. Complementing the often nonintuitive insights (e.g., a team member may be viewed as an ineffective contributor in one collaborative context, yet may prove an effective contributor to the same team under different collaborative conditions; Kuljanin, 2011) gained through simulation techniques with observations of actual team interactions enables exploration of potent behavioral mechanisms that can be targeted for validation within human teams (J. P. Davis, Eisenhardt, & Bingham, 2007; Kozlowski et al., 2012). More specifically, simulation models can be developed that specify the manner by which various behavioral mechanisms (such as those specified by Bedwell et al., 2012) interact to produce patterns of interaction representative of team collaboration. If desired, competing models can also be simulated to produce a range of possible outcomes against which to compare. Core propositions, novel findings, and counterintuitive results would be primary targets for verification. Longitudinal data could then be collected that examine the extent to which the computational model's propositions and predicted outcomes are supported. On the basis of these results, subsequent refinements (e.g., change in algorithms which guide team interaction, introduction of new/different task/team boundary conditions, etc.) could be made to the model(s) to improve predictive capability and guide future research and theory on team interaction. Thus, by capitalizing on the strengths of direct (computational simulation) and indirect (lab/field observation) research designs for studying emergent phenomenon, one is far better equipped to concretely describe, diagnose, and target the specific behavioral processes critical to team collaboration in a manner conducive to both research and practical applications.

Discussion

Status of Emergence in Organizational Science

We began this article by highlighting the two fundamental systems processes in organizations—top-down cross-level contextual effects and bottom-up emergence—and describing the remarkable research neglect shown to emergent phenomena. Multilevel quantitative research has exploded in the literature over the past decade, but virtually all of that research is focused on cross-level relationships. To the extent that emergence is shown any attention at all in such research, it is *indirect* with respect to models of measurement and data aggregation for representing higher order constructs. A quantitative multilevel perspective on organizational science has advanced, but it is researching only half of the organizational system. Moreover, while there is a substantial amount of qualitative research that endeavors to explore aspects of emergence, it generally lacks precision with respect to specifying the underlying process mechanisms. Some of the most interesting and perplexing phenomena—those that emerge dynamically over time—remain shrouded in mystery.

There are a number of reasons behind this situation, some theoretical and others methodological, but on balance we think that the primary reasons are due to research design limitations. As we illustrate in Table 1, there are a wide range of team process phenomena that are conceptualized as emergent. Beyond our focus on teams, there is an even broader array of organizational processes at many levels that are viewed as emergent (e.g., Weinhardt & Vancouver, 2012). That is a lot of raw substantive material. There is a substantial amount of theoretical attention to emergence in the sociological literature (e.g., Greve, 2012; Sawyer, 2001), a foundation of qualitative research (e.g., Orlikowski, 2002), and even agent-based modeling exemplars (e.g., Levine & Prietula, 2012). Moreover, there are extant multilevel theoretical and measurement frameworks for characterizing emergence (e.g., Bliese et al., 2007; Chan, 1998; Chen et al., 2004; Chen et al., 2005; Kozlowski & Klein, 2000) that can serve as theoretical points of departure. There is sufficient theoretical material, so the problem must lie elsewhere. We think "elsewhere" lies with research design constraints.

As we highlighted previously, there are two primary research design challenges that must be surmounted for emergence as a dynamic process to be a target for empirical research. First, capturing emergence necessitates studying social units that are new and ill formed, where interaction processes have yet to beget the emergence of macrostructures that then shape processes (Epstein, 1999). Although this is tractable in laboratory research (with its attendant limitations), it is very difficult to do in real-world settings.[6] Organizational science has relatively limited knowledge about emergence, and some basic expertise has to be acquired. Second, emergence unfolds dynamically through the interaction of individuals in a given context. One can assess such processes interpretively using qualitative methods, but to represent them with multilevel data is more challenging. Thus, to capture the dynamics of process mechanisms, it is necessary to collect data at a sampling frequency that is calibrated to the rate at which emergence evolves. Generally speaking, that means using research designs that generate observations at high frequencies and over lengthy periods. It is fair to say that neither of these requirements is a strong suit of the dominant research design disciplines of correlational and experimental research.

Both methodological issues are limitations in the conventional quantitative methods research design "toolbox." Basically, researchers have adapted conventional designs as best they can, but the underlying problem is that the designs do not align well with and do not capture the dynamic process mechanisms that are at the core of emergence. As Ilgen and Hulin (2000, p. 276) note,

> When cognitive and behavioral processes generate regular and relatively uninterrupted change, when constructs and their manifestations relate to each other linearly, when feedback or "feedacross" from outcomes onto antecedents of the next behavioral or cognitive episode are weak or inconsistent, and when the number of relevant constructs is limited, the two methods may provide useful data that allow us to estimate processes or event histories in organizational and individual space. But, the disciplines reach their limits when confronting data generated by stochastic, dynamic, nonlinear processes.

Computational Modeling: Advancing Quantitative Research on Emergence

Although conventional correlational and experimental research methods are challenged with respect to studying emergence, computational modeling and agent-based simulation offer distinct *theoretical and methodological* advantages for *direct* investigation of the dynamic micro processes that yield emergent macrostructures. With respect to theory, computational modeling necessitates a formal specification of the underlying process mechanisms reflecting human interaction that determine the nature of the emergence process. As currently constructed, most theories in organizational behavior are "word theories." Paraphrasing J. H. Davis (2000, p. 218), they are based on natural language, rich in metaphor, and lavishly nuanced, but lacking in sufficient precision for this degree of specification. Thus, integrating computational modeling/agent-based simulation with the dominant research designs would necessitate greater theoretical parsimony and precision. Although some might be concerned that the richness of social behavior would be stripped from theoretical constructions, we think that focusing on fundamental process mechanisms would actually help develop more elegant, informative, and powerful theories. The intent is to supplement, not replace, existing approaches.

Moreover, the methodological advantages of computational modeling, which include temporal sensitivity, high sampling frequencies, and wide scope, make it very useful as a method for conducting virtual experiments designed to build and extend theory. Computational modeling is temporally sensitive. Time is abstract, represented by event cycles in the computational model. Thus, it allows any time frame that is theoretically meaningful (moments, days, months, and/or years) to be modeled. In addition, models can be constructed that assume any position in a social space. For emergence, the typical focus would be on unit members with no prior history, but other configurations can be modeled if they make theoretical sense and are of interest. Thus, one could model the effects of shocks (e.g., changes in environments, technology, structure, tasks, etc.) on interaction processes and the emergence of adaptive responses. Computational modeling allows exceptionally high sampling rates that are commensurate with the theoretically determined rate of change for the phenomenon of interest. There are no missing observations with respect to change of system states. It simulates the fundamental time clock for the phenomenon of interest. Finally, computational modeling can encompass the entire scope of theoretical variability for factors relevant to the phenomenon of interest; this is very difficult to achieve with conventional research designs. For example, it is very challenging to research team composition effects simply because it is hard to get sufficient representation and variance across all potentially relevant composition factors (e.g., surface and deep-level diversity). Consequently, they tend to be studied one at a time. Computational modeling would allow any number of composition factors to be modeled simultaneously.

These advantages make computational modeling a viable research design tool for conducting virtual experiments. Theoretically based process mechanisms for emergence are specified, parameter values are estimated from existing research, theoretically relevant individual (entity level) and contextual factors are specified, and then this theoretical space is systematically examined virtually using agent-based simulation. Novel findings provide a basis for theory building and extension. Of course, key propositions that are identified using virtual experimentation need to be verified using real-world analogs (lab experimentation) or observation (field data). By better focusing such research, findings are likely to be more precise and informative. In addition, targeted empirical findings can then be used to increase the precision of the computational model by using observations to update parameter values and to add additional emergence process mechanisms to the computational model. We are not calling for computational modeling to replace conventional research methods. Rather, we explicate how together correlational, experimental, and computational modeling research designs can be used to elucidate the dynamics of emergence, and other, organizational processes.

Recommendations

We recognize that one of the biggest challenges for innovation in research design is simply making researchers aware of the capabilities of new research methods and providing them with models for implementation. Those are key reasons why quantitative multilevel research is now a mainstream method; those issues were addressed. We have endeavored to address these issues in this article by explicating the advantages of an integrated approach and by providing three specific exemplars. We are using the integrated approach we have described in our research program, and we are finding it to be highly informative (Kozlowski et al., 2012). We close with general recommendations to help

Table 2. Recommendations for Investigating Emergent Phenomena.

Research Program Phase	Recommendations
Develop the conceptual foundation for emergence	
Identify or select an emergent phenomenon of interest	• Incorporate core conceptual foci as criteria for selection • Use Table 1 as a source for potential research targets • Extend consideration to additional phenomena beyond Table 1 • Extend consideration to the macro level
Specify theoretical process mechanisms	• What are the primary micro-process mechanisms that account for emergence for the phenomenon of interest? • How do patterns of emergence evolve for the phenomenon of interest? • What are the primary antecedents that shape the nature of the emergence process? • What kinds of shocks shape or substantially change the nature of the emergence process?
Specify the resulting nature of emergence and the forms/types that should theoretically manifest based on the underlying process	• Use theoretical models and extant frameworks as guides ○ Bliese et al. (2007); Chan (1998); Chen et al. (2004)—construct/measurement models ○ Kozlowski and Klein (2000)—typology of emergent phenomena ○ Morgeson and Hofmann (1999)—structural and functional equivalence
Integration: virtual experimentation, verification, and theory building	
Theory building phase: conduct "virtual" experiments using computational modeling/agent-based simulation	• Systematically examine the theoretical space • Novel patterns or unusual regularities suggest candidates for theory building and verification
Verify theoretical extensions using correlational and experimental research designs	• Model and test new hypotheses with real-world data • Examine "generative sufficiency" of primary process mechanisms to create emergent phenomena with fidelity to real-world emergents
Refine and extend the computational model	• Enhance the precision of model parameters using real-world observations • Add complexity—incorporate additional mechanisms
Advance organizational science: iterate the process of virtual experimentation, theory building, and verification	• Continue this process utilizing all three research disciplines: computational modeling, correlational, and experimental research

guide other researchers who may wish to consider implementing the integrated, hybrid approach we have advanced.

Table 2 presents recommendations for studying emergent phenomena organized into those that are conceptual—*develop the conceptual foundation for emergence*—and those relevant to integrating computational modeling and conventional designs—*integration: virtual experimentation, verification, and theory building*. Within these two broad categories, we link the *research program phase* to specific *recommendations* for implementation.

Develop the Conceptual Foundation. The first step is to *identify or select an emergent phenomenon of interest.* In selecting a phenomenon to study, it is important that the researcher is sensitive to the core conceptual foci—multilevel, process oriented, and temporally sensitive—we discussed previously. These characteristics should be explicitly specified. Table 1 provides one potentially useful source for identifying such phenomena for study. Furthermore, the three exemplars we analyzed provide further theoretical specification and design ideas for research focused on emergence. Beyond these specific recommended targets, many more abound as a substantial proportion of theory in organizational behavior is multilevel, process oriented, and temporal. Learning, socialization, and development are possible research targets. Leadership, culture, and climate are targets. And, as we have noted, there is a substantial qualitative research foundation on which to draw. There are simply a lot of potential targets for research focused on emergence because it is ubiquitous in organizational behavior. In selecting potential targets beyond those identified in Table 1, we suggest that the interested researcher focus on middle range theory (Pinder & Moore, 1980) to ensure that the research target is broad enough to be meaningful, but sufficiently constrained so that assumptions regarding the phenomenon are explicit and that boundary conditions are specified. J. P. Davis et al. (2007) suggest that "simple" theories—those with few constructs, but with basic processes mapped—are useful targets. Whether the theories are simple or complex, basic process mechanisms need to be specified.

The second step is to *specify theoretical process mechanisms.* The theoretical focus here is on the relevant elemental content—*what* is the "stuff" that entities are to communicate or exchange—and the interaction processes that describe *how* it is communicated or exchanged (Kozlowski & Klein, 2000). This specification provides the architecture for the design of agents and the parameters that guide their interactions. It must be sufficiently precise to be translated into a set of logical statements or formal mathematical representations. For example, as we described for the STMM example, McComb (2007) provided a detailed process model specification of STMM convergence, which Dionne et al. (2010) then used as a basis to specify a computational simulation to model factors that shape STMM emergence. Similarly, for the social dilemma example, two specific process mechanisms—social learning and success-driven migration—were postulated as the underpinnings for the emergence of cooperative clusters (Helbing et al., 2011). For collaboration, Kuljanin (2011) specified different interaction structures and preferences for team cooperation. As noted previously, simple theories are likely to be easier to specify than complex theories. However, the key for specification is how well the theory—simple or complex—describes the underlying processes of interaction and exchange. Once the researcher has specified the focal process mechanisms, potential antecedents and moderating factors need to be specified and incorporated into the computational model. We have listed a core set of basic research questions to guide this specification process.

The third step is to specify the nature of the emergence process and the forms that are expected to manifest based on the underlying process mechanisms. Here researchers have a reasonable point of departure by drawing on qualitative research and referencing extant multilevel frameworks. Chan (1998), for example, provides a range of composition models that are relevant for composition forms of emergence as well as dispersion and process models. The Kozlowski and Klein (2000) emergence typology postulates theoretically based emergence processes and emergent forms across a continuum ranging from convergent composition forms to divergent and configural compilation forms. Morgeson and Hofmann (1999) highlight the structural and functional equivalence issues relevant to distinguishing composition and compilation forms. These three treatments are conceptually consistent, but have different emphases. In particular, Kozlowski and Klein (2000) emphasize that given phenomena may have equifinal forms of emergence. Thus, factors that account for why emergence unfolds in different ways under different conditions becomes an important theoretical focus. Moreover, they view nonlinear compilation forms of emergence as more complex—and potentially more interesting—than the well-researched convergent forms. They provide fairly detailed explanations of the underlying emergence processes that can serve as a point of departure to guide theoretical models for specification.

Integration: Virtual Experimentation, Verification, and Theory Building. Having developed the conceptual foundation that identifies the phenomenon, specifies its underlying emergence processes, antecedents, and moderators, and characterizes its expected forms of manifestation, the researcher is now equipped to integrate research designs. The first step in this phase is to conduct *virtual experimentation*. Agents are research subjects for virtual experimentation. The antecedent factors are targets for experimental manipulation. Manipulation parameter ranges can be selected to be commensurate with known or expected real-world values. This is useful when one wishes to generalize inferences to real-world targets (cautiously, of course, with additional steps we shall outline). Alternatively, one may examine theoretically relevant ranges. This is useful when one wishes to examine emergence under novel conditions and/or to discover novel forms of emergence. Shocks serve as potential "moderators" that can be manipulated or, alternatively, that serve as boundary conditions. A well-mapped theoretical space (i.e., process mechanisms, antecedents, and shocks) is then systematically researched. This can involve considerable simulation. For example, in the study on collaboration discussed previously, Kuljanin (2011) simulated 1,000 five-person teams performing 100,000 performance episodes across 216 experimental conditions that consisted of 24 team collaboration conditions (i.e., 3 sets of preferences, 4 collaboration networks, 2 interaction protocols) by 9 individual competency conditions (i.e., 3 sets of task work skills, 3 sets of teamwork skills). The agents do the heavy lifting and the theoretical space is fully examined.

Just as in conventional research, observed regularities in antecedent—outcome effects (i.e., forms of emergence) and modification of the process by shocks are candidates for inference. Novel, unusual, or unexpected outcomes for emergence prompt theory building and experimentation. For example, in our research on team learning and knowledge emergence modeled via agent-based simulation, we observed that within-team variability in learning rates and knowledge sharing strategies were detrimental to the emergence of shared team knowledge. This then shaped follow-up research we conducted with human teams that targeted the process problems observed in the agent-based teams (Kozlowski et al., 2012).

Whether the simulation findings extend theory based on novel findings or conform to theoretical expectations, the next step of *verifying simulation findings* using correlational or experimental research is critical. The point of the prior step of systematically mapping the theoretical space is to eliminate unlikely possibilities and to focus attention on the more likely emergent relationships. This is where conducting conventional research to verify the findings is important. Having modeled an emergent phenomenon with simulation is one thing; now one has to demonstrate that the inferences based on virtual experimentation will hold with real social data. Thus, for example, we previously highlighted how Van Lange et al. (2002) conducted conventional experiments that supported findings from prior social dilemma simulations (Kollock, 1993). Designing verification studies is challenging because one is typically not going to have the same theoretical scope (i.e., number of factors to examine simultaneously), sample size and power, or high frequency of measurement in real-world research as can be obtained with simulation. But one does have insight from the simulation findings, and that makes targeting research design and measurement more precise. That is, simulation findings can be used to target where in the emergence process transitions, particular intermediate states, or other "markers" of emergence occur that can be isolated for measurement and analysis.

As the researcher conducts human observation and/or experimentation—with a goal of ensuring that fundamental process mechanisms are operating—for purposes of establishing model fidelity and verification, the research is also collecting data that can be used for the next step, which is to *refine and extend the computational model*. Essentially, if the fundamental process mechanisms are instantiated in the research, then the information provided by real-world research can be used to add precision to the computational model parameter values, which will yield closer correspondence between the model and the behavior of interest. In addition, sparse computational models that show good fidelity with real-world data can be incremented in complexity and precision with the incorporation of additional process mechanisms. The goal is not to represent the complexity of extant theory per se. Rather, parsimony remains a guiding principle. The theory building and modeling effort should be only as complicated as is necessary to account for the emergent phenomena of interest and to demonstrate its fidelity with the real world. Once that is achieved, the computational model has the potential to be a primary experimental platform for research and exploration.

Conclusion

Organizational science has advanced substantially over the past century. For most of its development, qualitative research has been the primary means for investigating the systemic character of organizations, especially emergent phenomena. As quantitative multilevel research begins to probe across multiple organizational levels and time to better comprehend systems, process dynamics, and emergence, it is increasingly clear that the traditional twin pillars of scientific research design—correlational and experimental methods—are limited in what they can reveal. We think that there is a need to enlarge the array of research design approaches and that a compelling case can be made for better incorporating computational modeling/and agent-based simulation in our methodological toolbox. With intelligent coordination between conventional approaches and computational modeling, a more powerful toolkit can be used by researchers to directly examine the dynamics of emergence. We, and others, are probing that frontier. We hope this article will stimulate others to join us to advance quantitative methods in organizational science.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: We gratefully acknowledge the Office of Naval Research (ONR), Command Decision Making (CDM) Program (N00014-09-1-0519, S. W. J. Kozlowski and G. T. Chao, principal investigators) for support of this research. Any opinions, findings, and conclusions or recommendations expressed are those of the authors and do not necessarily reflect the views of the CDM Program or ONR.

Notes

1. Micro refers to individual, meso refers to the group or team, and macro refers to the organization and higher levels.
2. We use the term *multilevel* in a generic sense, to encompass cross-level and multilevel research.
3. See Epstein (1999) for a concise discussion and refutation of emergentism.
4. Additive models use sums or means of lower level units (individuals) to represent constructs at a higher level (groups); they make no assumptions about isomorphism or similarity of the construct across levels. Direct consensus and referent-shift models incorporate assumptions of isomorphism and use restricted within-group variance (i.e., consistency or consensus) to support aggregation using the unit mean to the higher level, using data referring to the lower level directly (e.g., rate your perceptions) or to a referent-shift (e.g., rate how other group members perceive).
5. Because of their highly similar measurement approaches, the issues in the motivation and affect category are virtually identical to those in the cognitive category. We just illustrated for cognitive.

6. It is of course also possible to study emergence in existing social systems. For example, one could be interested in understanding how environmental change (e.g., task, technology, structure, etc.) forces change and adaptation in existing social systems (Kozlowski, Gully, Nason, & Smith, 1999). That is a form of emergence too, but it will be very difficult to characterize that emergence without knowledge of the extant process.

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