Capturing the Multilevel Dynamics of Emergence:

Computational Modeling, Simulation, and Virtual Experimentation

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Abstract

Emergent phenomena – those that manifest bottom-up from the psychological characteristics, perceptions, and interactions among individuals – are a fundamental dynamic process in multilevel theory, but have been treated in a very limited way in the research literature. In particular, treatments are largely assumed (rather than observed directly), retrospective, and static. This paper describes a research paradigm designed to examine directly the dynamics of micro-meso – individual, dyad, and team – emergent phenomena. We identify, describe, and illustrate the sequence of theoretical, measurement, computational, data analytic, and systematic research activities that are necessary to operationalize and utilize the paradigm. We illustrate the paradigm development process using our research, focused on learning and team knowledge emergence, and highlight key *design principles* that can be applied to examine other emergent phenomena in teams. We conclude with a discussion of contributions, strengths and limitations, and generalization of the approach to other emergent phenomena in teams.

Capturing the Multilevel Dynamics of Emergence:

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One of the key challenges for making progress in the organizational sciences is enlarging the arsenal of research tools typically employed by investigators. There is no question that substantial advances in research design and methods have occurred since the inception of organizational research over a century ago. However, it is also the case that the over reliance on questionnaire-based measures, rather than more direct behavioral assessments, and cross-sectional designs, rather than designs that capture the dynamics of phenomena, are major impediments to scientific advances. Capturing how phenomena develop, evolve dynamically over time, and emerge as collective properties is on the frontier of multilevel theory and developing research capabilities to investigate such dynamics directly is central to advancing organizational science as a systemic, multilevel discipline.

We assert that quantitative modeling the multilevel[1] dynamics of emergent phenomena ought to be a core competency of organizational science[2]. Multilevel research has expanded rapidly since the turn of the 21st century (Kozlowski, 2012b). Much multilevel research is based on theoretical *assumptions* that describe how lower-level phenomena emerge as collective properties. For example, unit climate is assumed to coalesce from among individuals in the unit sharing their perceptions or team mental models are assumed to become shared via teamwork interaction (Kozlowski & Klein, 2000). We have well-established statistical procedures for evaluating whether such constructs have emerged retrospectively - after the fact – in line with theoretical assumptions (Bliese, 2000; Chan, 1998; LeBreton & Senter, 2008). However, emergence as a *dynamic process* with interplays across system levels has rarely been studied directly in quantitative empirical research. Rather, it is assumed and treated in a static fashion (Kozlowski, 2012a; Kozlowski & Chao, 2012b). *The purpose of this paper is to describe the critical conceptual and methodological underpinnings – an architecture – to develop a paradigm for examining emergence as a dynamic, multilevel phenomenon.*

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[1] We use the term "multilevel" in a generic sense, to encompass cross-level and multilevel research.
[2] We acknowledge that much qualitative research addresses emergence directly, but our focus is on quantitative measurement and modeling of emergent phenomena (Kozlowski & Chao, 2012b).

We use the word *paradigm* to describe our approach as *an integration of substantive and multilevel theory, research design, measurement, and analytics.* We elaborate more on this subsequently, but we want to be clear that we are using the term in this specific way (small p) and our usage should not be confused with Kuhn's (1962) broader philosophy of science meaning (scientific paradigm as big P). As with any research paradigm, the specific theoretical, methodological, and measurement tools we have developed are contextualized to a particular problem domain. A research paradigm is purposefully designed to study specific, bounded phenomena. Thus, we use our foci of interest – *learning in collaborative teams and the emergence of team knowledge* – as the vehicle for explicating the specifics of the research paradigm and to provide a substantive context for our descriptions of the theory, research tools, and analytical approach we have developed. Nevertheless, the *research design principles* that we highlight are generalizable to other cognitive, motivational, and behavioral phenomena that emerge through individual interaction in team and higher level contexts. Elsewhere, we have provided the theoretical foundation of this approach and have described how it can be applied to a sampling of emergent team phenomena – team mental models, social dilemmas, and team collaboration (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013). Our purpose in this paper is to provide a primer; a model of how to do it. We explicate the key design principles that underlie this architecture, and illustrate their application using our research as an example, so other investigators may model the approach to develop their own paradigms to study emergent phenomena of interest. Explicating how our approach can be applied to other emergent and dynamic phenomena in teams will be discussed in the concluding section of the paper.

The paper is structured as follows. First, we provide a concise overview of the treatment of emergence in micro-meso organizational psychology and behavior (OPB) research. This is intended to establish the necessity of focusing on the dynamics of emergence to advance multilevel OPB theory and research. Next, we describe the core components of the paradigm architecture, which include theoretical synthesis, metrics, process mechanisms, computational modeling, virtual experimentation, human simulation, data analytic considerations, and

systematic research. Finally, we conclude with potential extensions of our paradigm to other micro-meso phenomena and provide recommendations for implementation.

Emergence in Micro and Meso Organizational Behavior Research

Two fundamental system processes cut across the levels of organizations in multilevel theory. First, contextual effects are top-down processes that shape and constrain lower-level phenomena that are embedded or nested in the higher level context. Second, emergent processes percolate from the bottom-up. "*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*" (Kozlowski & Klein, 2000, p. 55). Emergence comprises *"… stable macroscopic patterns arising from the local interaction of agents"* (Epstein, 1999, p. 53). Organizational system theorists have long recognized the duality of process (emergence) and structure (context) as reciprocal forces. Over time, bottom-up interaction processes emerge as structures that shape subsequent interactions (Allport, 1954; Katz & Kahn, 1966). Together, these two primary forces of emergence and context encompass system behavior and are, thus, fundamental lenses for understanding organizational behaviors as multilevel phenomena.

The development of theoretical principles, improved methodological guidance, and statistical modeling advances has led to an explosion of multilevel theory and research in the OPB literature over the last decade (Kozlowski, 2012b). However, the vast majority of this research is focused on top-down, cross-level, contextual effects. To the extent that emergence as defined above is considered, it is primarily treated as an *assumed* and *unobserved* process responsible for the manifestation of a collective construct that has originated from the lower level (Kozlowski & Chao, 2012b). Such "emergent states" in teams (Marks, Mathieu, & Zaccaro, 2001) often focus on "team processes" represented as collective constructs that originate from individual cognition, motivation, affect, and behavior (e.g., team mental models, collective efficacy, group mood, and coordination, respectively). Researchers specify a composition (or compilation) theory as advised to guide how the "team process or emergent state" is

represented as a construct for research purposes (Kozlowski & Klein, 2000), but the dynamic multilevel process of emergence is not directly observed. Rather, after emergence has unfolded, researchers collect retrospective perceptions on the phenomenon of interest and verify theoretical assumptions by assessing restricted within unit variance for composition constructs (Bliese, 2000; Chan, 1998) and variability patterns or other markers for compilation constructs (Kozlowski & Klein, 2000). Thus, emergence is assumed theoretically and the assessment or representation of the emerged construct is static.

To be clear, this dominant approach is perfectly legitimate for evaluating cross-level and multilevel models. An examination of static (and presumably stable) relations among emerged "team process" constructs, their antecedents at the same or higher levels, contextual moderators, and team outcomes provide important empirical building blocks for aiding understanding and refining theory. Such research should continue to be conducted. However, such research does not advance understanding of emergence as a multilevel dynamic process, which is what we wish to advance. Our focus is on understanding the dynamics of emergence per se, on capturing the process directly; rather than its (assumed) end-state representation as a static construct.

In addition to assuming emergence as a process, there is another key limitation in much current multilevel research. Convergent, composition phenomena – perhaps because they are intuitively appealing, widely applicable, and well established – dominate the research. Far less attention is devoted to emergent phenomena that are compilational or configural in form (Cronin, Weingart, & Todorova, 2011; Kozlowski & Chao, 2012b). This neglect is important because Kozlowski and Klein (2000) made a point of emphasizing that emergent forms are not fixed, but variable in nature; they often evolve and change. Team knowledge, for example, is represented in the literature by a team mental model (TMM), conceptually a composition construct, and transactive memory (TM), conceptually a compilation construct[3]. Yet, as team members begin to learn their roles, they are likely to have very different knowledge initially

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[3] Although the most popular measure of TM (Lewis, 2003), is treated much like a composition construct.

(consistent with TM) and only later will that knowledge converge around shared understandings (consistent with TMM). Thus, capturing the emergence process as a dynamic phenomenon necessitates an approach that can range across the spectrum of compilation (e.g., TM) and composition (e.g., TMM) emergent forms, rather than treating the types of emergence as fixed categories firmly associated with particular constructs. Because emergence is a process, not a construct per se, its products (i.e., construct representations) may be unstable, ranging across the continuum of emergent forms, evolving and devolving with respect to collective constructs. Although stability in the emerged form is typically assumed in research, this assumption may not be correct and cannot be firmly substantiated without direct observation. Since emergence is so rarely studied directly, the extent to which emerged phenomena are stable or unstable, and the forces that influence stability and instability, are essentially unknowns.

Why is the treatment of emergence – *a fundamental multilevel process* – so limited in OPB research? We think it is a consequence of the research paradigms typically used in OPB. Kozlowski and Klein (2000) noted that top-down, cross-level effects often manifest rapidly and, thus, can be captured using cross-sectional survey designs, whereas bottom up phenomena take time to manifest and, therefore, necessitate longitudinal designs if the dynamics of emergence are to be captured. Cross-sectional, survey research designs predominate in the multilevel OPB literature. Intensive longitudinal designs that necessitate many, many measurements are very challenging to execute in organizational settings using survey-based methods. However, there are numerous phenomena that emerge in more constrained settings and time frames that are ideal targets for the development of conceptual frameworks, research tools, and measurement techniques that can capture the dynamics of emergence. Developing a laboratory and simulation-based paradigm for modeling emergence would provide a foundation for advancing understanding of emergence as a fundamental micro-meso process and would provide a basis for developing meta-theoretical principles that elucidate the process mechanisms underlying the dynamics of emergence. It would serve as a basis for initiating research on emergence *as a dynamic process*, developing an understanding of basic process

mechanisms that drive multilevel emergence, and providing an exemplar for generalizing to other emergent phenomena relevant to multilevel OPB. We now turn attention to the specifics of the architecture of our paradigm.

A Paradigm for Modeling Emergence in Teams

Overview. We describe our approach as a *paradigm* because it entails an integration of a theoretical framework focused on the substantive problem domain and multilevel phenomena of interest; process mechanisms and metrics to capture meaningful variation in the phenomena; and aligned research design, data collection methodologies, and analytical techniques. A few exemplars highlight the paradigm elements and the key role that is often played by a *synthetic world* – a simulation that emulates core psychological characteristics of the phenomena of interest. That is, a simulation that possesses psychological fidelity with the phenomena of interest (Kozlowski & DeShon, 2004). For example, in their systematic research on self-regulation, learning, and performance adaptation, Bell and Kozlowski developed an integrated paradigm of theory and research design constructed around the TANDEM simulation (e.g., Bell & Kozlowski, 2010; Kozlowski, Toney, Mullins, Weissbein, Brown, & Bell, 2001). At the team level, Ilgen, Hollenbeck, and their colleagues developed an integrated paradigm around the TIDE[2] simulation (e.g., Hollenbeck, Ilgen, Sego, Hedlund, Major, & Phillips, 1995; Ilgen, Major, Hollenbeck, & Sego, 1995) to examine leader decision making in teams and, later, another based on MSU-DDD used to examine asymmetric structural adaption in teams (e.g., Johnson, Hollenbeck, Ilgen, Humphrey, Meyer, & Jundt, 2006). DeShon and colleagues developed a paradigm to study multilevel – individual *and* team – goal regulation and performance using TEAMSim (DeShon, Kozlowski, Schmidt, Milner, & Wiechmann, 2004). In each of these examples, the simulation was constructed so as to align the theory of the phenomena with research design and measurement metrics. Unfortunately, investigators often select a simulated task off-the-shelf without recognizing that the psychological and group phenomena the task emulates, requisite metrics, and design considerations need to be integrated with the theory of the phenomenon (Kozlowski, in press).

Our theory and research focus is on learning in team contexts and the emergence of team knowledge that can be applied to solve consequential problems. Because our research focus is basic, the paradigm is laboratory, computational-agent, and simulation based. In any paradigm, the research target determines specifics and so our description is necessarily steeped in that focus. Nonetheless, because the theory, emergence process mechanisms, and measurement metrics we developed to investigate team knowledge emergence are additive in nature, the paradigm is directly generalizable to other team and higher level emergent phenomena that are pooled. For example, the team behaviors represented in the Marks, Mathieu, and Zaccaro (2001) process taxonomy are additive in nature. Thus, the paradigm we discuss can be readily adapted to team process behaviors. Moreover, the paradigm development methodology can be applied to model and investigate a full range of emergent phenomena in teams (Kozlowski et al., 2013). Investigators simply need to specify appropriate theoretical process mechanisms and then apply the architecture and design principles.

In the material that follows, we explicate the paradigm development process. We use our research focus – learning in collaborative teams, the dynamics of knowledge emergence, and the evolution of team knowledge – as a vehicle to explain the (a) *sequence of steps* and (b) *key design principles* relevant to each step. The substantive focus enables a more concrete description of the paradigm components. However, we want to emphasize that the basic process we have employed can be applied to other emergent phenomena as noted above.

The architecture for paradigm development and operationalization are illustrated in the top portion of Figure 1. There are important aspects of the research paradigm development process that merit emphasis. First, the synthesis of substantive theory and the principles of multilevel theory are the conceptual drivers of the process. Second, several key steps occur in parallel. Specifying the theoretical forms of emergence and developing metrics to capture them, and specifying substantive process mechanisms are crafted in parallel. Similarly, the development of a computational model and the design of a human simulation, are highly integrated and therefore proceed in parallel. Finally, systematic research and data analytics

generate empirical knowledge that feed back to (a) advance precision in the computational model and human simulation design and (b) refine the theoretical forms of emergence, metrics, and process mechanisms.

<Insert Figure 1 about here>

Each step in the sequence entails specific *design principles.* These are conceptual issues critical to the effective execution of each step in the paradigm development process. The design principles capture conceptual goals and issues that should drive realization of each step. As we explicate our approach, we first make the design principles for each step, illustrated in the top portion of Figure 1, explicit. Then, to contextualize and illustrate the application of the design principles, we use our research focus on team knowledge emergence, illustrated in the lower portion of Figure 1, to demonstrate how the design principles are incorporated in the paradigm development process. In that sense, the design principles we highlight represent recommended guidelines for investigators who are inspired to translate our approach to phenomena that are of interest to them. The steps in the paradigm development sequence and their associated design principles are listed in more detail in Table 1.

<Insert Table 1 about here>

Synthesize a theory of the emergent phenomenon of interest. By its very nature, studying emergence necessitates a synthesis of a substantive phenomenon (e.g., team knowledge, behavioral processes, cohesion; whatever is of interest to the investigator) with the meta-principles of multilevel theory – specifically, those principles focused on "elemental" content, interaction processes, and resulting forms of emergent phenomena (Kozlowski & Klein, 2000). One *design principle* for paradigm development is that the substantive theoretical focus has to fit the temporal frame and context of the research approach. For example, our focus is on studying team learning in a lab setting. A substantial research foundation provides evidence that individual learning and a variety of team processes can be effectively modeled in lab simulations (e.g., Bell & Kozlowski, 2010; DeShon et al., 2004: Hollenbeck et al., 1995). Thus, we have clear indications that middle range theory (Pinder & Moore, 1980) focused on team learning and

collaboration can be meaningfully investigated in the constrained time frames of lab research (e.g., two to three hours). A second *design principle* is that the substantive theory has to have sufficient articulation of the basic elemental content (i.e., what is exchanged) and micro-meso process mechanisms (i.e., how it is exchanged) underlying the dynamics of emergence. In general, substantive theories that have a developmental and / or temporal focus will be easier to integrate with multilevel theory principles, whereas static theories will necessitate more conceptual extension to provide the missing details.

With respect to our theoretical synthesis, collaborative learning processes and team knowledge outcomes are emergent phenomena in team contexts. They transcend individuals, encompassing multiple levels – individual, dyad, team. Thus, the conceptual foundation of our research paradigm is based on a synthesis of a theory of macrocognition (Fiore, Rosen, Smith-Jentsch, Salas, Letsky, & Warner, 2010), which is relevant for conceptualizing team learning processes and knowledge outcomes, and multilevel theory (Kozlowski & Klein, 2000), which is relevant for developing representations of the emergent processes and resulting emergent forms that manifest across levels – bottom up – dynamically over time. Collective knowledge is shaped by individual learning and interaction. Individuals acquire relevant knowledge, share it with each other, and team knowledge emerges dynamically (Fiore et al., 2010; Kozlowski & Chao, 2012a).

Macrocognition is a conceptualization of team learning that developed in the human factors literature and has been applied to understand collaborative learning and decision making in complex, uncertain, and consequential problem domains (Fiore et al., 2010). It is consistent with prior theoretical work that view team learning as a process and teams as processors of information who are subject to a variety of perceptual and motivational biases that often yield suboptimal decisions (e.g., Bell, Kozlowski, & Blawaith, 2012; De Dreu, Nijstad, & van Knippenberg, 2008; Hinsz, Tindale, & Vollrath, 1997; Stasser, 1999; Stasser & Titus, 1985). Consistent with the design principles highlighted previously, the theory of macrocognition developed by Fiore and colleagues is germane to our focus because it conforms to key meta-

theoretical assumptions that are critical for understanding team learning and knowledge emergence: Learning processes and knowledge outcomes are distinct, and it is explicitly multilevel (individual and team), dynamic (iterative), and emergent in nature (individual to dyadic to team level; Bell et al., 2012). Moreover, knowledge emergence for bounded problem domains can be modeled in the constrained time frames of laboratory research.

Macrocognition is most applicable to problem domains where team members have distinct roles, expertise, and – therefore – access to unique knowledge. In these domains, team members have to acquire information relevant to their role expertise and then that information has to be made available to the team for problem solving. This conforms to the widely applicable "hidden profile" team decision structure (Stasser, 1999; Stasser & Titus, 1985). Another key assumption of the theory is that knowledge has to be shared, accepted, and learned by the team collectively – *externalized* – to be applicable for problem solving. Externalization is described as a process by which *internalized knowledge* about a problem domain acquired by each team member is transformed to *externalized knowledge* that is shared by the collective (Fiore et al., 2010). This process is iterative with feedback loops, and knowledge emerges upwards across levels. *Individual knowledge building processes* (i.e., learning) create *internalized knowledge* that is a property of each team member. Individuals interact, discuss, and exchange the internalized knowledge they acquire via *team knowledge building processes*. This collaboration yields *externalized team knowledge* held by the team collectively that can be applied to make decisions. There is also an inherent temporal dynamic to this process in that team members initially have to focus on the acquisition of unique problem relevant knowledge and, then, as they develop internalized knowledge, shift emphasis to knowledge sharing and team knowledge building that creates externalized knowledge.

Specify the theoretical forms of emergence and develop metrics to capture them. A *design principle* is that there has to be sufficient theoretical precision to define and differentiate the forms of emergence relevant to the substantive phenomenon. If the forms of emergence are not well articulated, it will be difficult or impossible to link them to distinct metrics or forms of

representation. Existing theoretical (Kozlowski & Klein, 2000) and measurement (Chan, 1998) typologies can be used to guide the linkage of emergence forms to representation. Another *design principle* is variation in forms of emergence. As we noted previously, extant research tends to treat emergence as fixed and stable, whereas emergent forms have the potential to evolve across the range of compilation to composition types as they manifest (Kozlowski & Klein, 2000). A third *design principle* is that the metrics that are developed have to capture the rate of emergence (i.e., evolution across different forms) so they need to possess an appropriate degree of resolution. In principle, this means that metrics should be targeted on the level of origin (i.e., the lowest level of interest; Kozlowski & Klein, 2000) and the frequency of measurement should be at a rate that is commensurate with the pace of emergence. If not, the metrics will lack sufficient resolution to capture the dynamics of the emergence process.

The theory of macrocognition by Fiore et al. (2010) provides a basis for specifying the forms of knowledge emergence that result from individual learning behavior and team interaction processes; in this case, behavior focused on learning and knowledge sharing. Theoretically derived forms of emergence then have to be linked to or aligned with specific representations or metrics that can capture emergence as a dynamic process. We developed a typology of team knowledge emergence that captures both discrete "snapshots" that characterize how knowledge is distributed across team members at any given point in time, as well as more dynamic representations that reflect variances in rates of acquisition and sharing both within and between teams (Kozlowski & Chao, 2012a). The underlying logic is analogous to that of making a motion picture. Each discrete frame of a film is a single shot of action. By linking the frames together at an appropriate sampling rate – 24 fps for motion picture film – one creates a representation of the action dynamics that emulates how it unfolded. The typology pulls apart discrete elements that capture the underpinnings of knowledge emergence in teams – much like the discrete frames of a film – and compiles patterns of frames to capture the dynamics of knowledge emergence in teams as a movie.

The metrics specified by the typology are multilevel, dynamic, and emergent and incorporate features of collective knowledge (i.e., team knowledge as a collective pool), team mental models (i.e., team knowledge as a shared property), and transactive memory (i.e., team knowledge as a configuration of distributed knowledge). The typology thus represents team knowledge as (a) *pools* of individual and collective (overlapping or shared) team knowledge; (b) *configurations* that capture patterns of distinct individual, dyadic, and collective knowledge; and (c) *variance* in the rates of knowledge building and its emergence at the team level, both within and across teams, over time.

The typology is conceptual in nature. Thus, operationalization of the knowledge types has to be contextualized in a task and relevant knowledge domain. The requirement for distributed expertise (i.e., distinct team member roles) means that team members have access to unique information consistent with their roles, as well as common information about the problem space that is available to all team members. This task structure conforms to the hidden profile paradigm developed by Stasser and his colleagues (Stasser, 1999; Stasser & Titus, 1985). One of the key findings from the voluminous research conducted on hidden profiles is that groups tend to focus on the common information available to all members during knowledge sharing and, as a result, attend less to the unique information (the hidden profile) that is important to decision quality; thus, group decisions are often suboptimal (Stasser, 1999). Conceptually, the knowledge typology is applicable to such hidden profile decision structures which encompass a wide range of group and team decision-making tasks.

The typology metrics are defined and linked to the macrocognitive model in Table 2. They are organized from individual to team level; discrete to dynamic. *Individual knowledge* is the proportion of the total knowledge pool (common and unique) held by each member at any point in time (individual level, internalized knowledge), but does not account for knowledge overlaps across members. The *knowledge pool* assesses the proportion of the total pool acquired by the team collectively and accounts for redundancy (team level *composition* measure, internalized and externalized knowledge). This metric captures knowledge that is held

collectively, but is not revealing of how it is configured across individuals, dyads, and the team as a whole. Metrics that capture *knowledge configuration* represent its pattern of distribution as a set of proportions (multilevel [individual, dyadic, team] *compilation* measures, internalized and externalized knowledge). This set of metrics capture discrete "snapshots" of team knowledge acquisition at any given point in time.

<Insert Table 2 about here>

The next set of metrics capture emergence dynamics as rates and variances. As team members learn about the problem space, share their individual knowledge, and learn from others, the configuration of knowledge – individual, dyadic, and team – emerges and evolves. This dynamic emergence is assessed as *knowledge acquisition* – the rate of growth of individual knowledge (individual level internalized and externalized knowledge). Many factors such as individual difference characteristics, team composition, and the situational context will affect the rate of individual knowledge acquisition, information sharing, and externalization. This yields *knowledge variability* in within team rates of knowledge acquisition (team level internalized and externalized knowledge). *Knowledge emergence* is captured within and between teams by assessing rates of growth for the knowledge pool, knowledge configuration, and knowledge variability (between team). This set of metrics represents how rapidly team members learn, share, and externalize knowledge. Teams that quickly build and externalize relevant knowledge are more likely to make better decisions in complex, ill-structured, and time limited situations.

Specify the substantive content, processes, and mechanisms. The substantive process mechanisms that are the theoretical "engine" of emergence are inherent in the substantive-multilevel theoretical synthesis. However, this aspect of paradigm development delves into the deep details. It focuses on the "elemental content" (i.e., the "stuff" of emergence – what content is exchanged) and the "rules" or process mechanisms that drive the dynamics of the emergent forms (Kozlowski & Chao, 2012b; Kozlowski et al., 2013; Kozlowski & Klein, 2000). Thus, unlike typical theory and research approaches in OPB, team processes are not a static mediating "box" in a model. The approach is more akin to that of cognitive psychology where process is

not represented by a box-and-arrow, construct-to-construct model. Rather, it is a specification of the *actual* psychological and/or behavioral actions at the lowest level of analysis (i.e., within individual) that contribute to the emergence of the phenomenon.

One *design principle* is to specify the elemental content. Kozlowski and Klein (2000) define elemental content as "the raw material of emergence" (p. 55). It is comprised of attributes that individuals hold (e.g., ability, personality), acquire (e.g., knowledge, perceptions, attitudes, affect), and / or exhibit (e.g., behaviors). It is the focal content of the substantive theory. It must be defined with sufficient precision to be tracked by the metrics. A second *design principle* is to specify the process mechanisms; the theoretically driven form of intersection, interaction, or exchange whereby elemental content from different individuals (or whatever your focal entity is) accumulates, converges, or clashes (Kozlowski & Klein, 2000). Process mechanisms are the engine of emergence dynamics and need to be defined with enough precision to guide a mathematical specification of the process for the agent-based simulation. A third *design principle* is that if there is variation in the forms of emergence that the phenomenon takes on as it evolves – as in our theory – it needs to be explicit in the process model. Finally, a fourth *design principle* is that the process model needs to be explicitly linked to the metrics.

Drawing on the theoretical foundation and the measurement typology, we developed a dynamic process model to specify the basic mechanisms and parameters that determine how individual team members incrementally *learn* problem-relevant knowledge and *share* that knowledge with other members as they collectively seek to solve the problem. This dynamic process model is essentially a "blueprint" for the basic mechanisms of macrocognition – learning, sharing, and externalization – that is then used in the next step to formalize a computational model. The process mechanisms are linked to the theoretical foundation and the knowledge typology. Thus, the forms of emergence span across the continuum of composition to compilation as team members initially hold unique knowledge that over time becomes shared across dyads (hence, is a compilation configuration) and incrementally becomes shared by the team as a collective (composition).

Our modeling approach assumes that team members have role expertise, but are naïve about the specific unique and common information that has to be acquired for a particular problem scenario. Thus, information is distributed as common (unlearned, but accessible to all) and unique to each team member. Unique information can only be learned by other team members when it has first been learned and then shared by the member with relevant expertise. Learning has primacy; team members cannot share what they do not know, so individual learning dominates the process initially. Learning, that is memorizing information, is effortful and it requires multiple exposures to information before it is internalized as accessible knowledge (e.g., Miller, 1956). Learning phases alternate iteratively with sharing phases, during which team members attempt to share their internalized knowledge with teammates. Like individual learning, it requires multiple exposures to information shared by others before it is acquired. It is also the case that learning indirectly is slower than learning from direct exposure (e.g., Corey, 1934). Thus, learning dominates knowledge acquisition in early phases as individual team members attempt to internalize their unique information, whereas sharing dominates the acquisition of knowledge in later phases as team members attempt to transfer what they learned to the team collectively.

Develop an agent-based, computational simulation. The computational simulation instantiates substantive content of interest; process mechanisms to guide interaction; and their linkage to emergent forms, evolution, and the metrics. Thus, the explicit specification of elemental content and process mechanisms is critical to operationalizing the agent-based simulation. One *design principle* is that the elemental content has to be represented in the computational code and the process mechanisms have to be formally represented as equations that specify how agents interact and exchange elemental content. In addition, process mechanisms have to be calibrated with parameters drawn from extant research or, as we shall describe later, from research within the paradigm. A second *design principle* is that the output from the agent-based, computational simulation – what emerges – has to be linked to the

emergence metrics in meaningful ways. In other words, simulation output has to be aligned with theoretical, process, and measurement models as a means to validate the model and metrics.

With respect to our paradigm, the next step utilized the mechanisms of the dynamic process model to specify a computational model that would instantiate the processes of individual knowledge acquisition, knowledge sharing, and the dynamic emergence of different forms or types of team knowledge. A computational model provides a theoretically-grounded, mathematical depiction of a phenomenon of interest that can be used to characterize the mechanisms by which a dynamic process unfolds (Busemeyer & Townsend, 1993; Hulin & Ilgen, 2000). Computational models utilize mathematical relationships (e.g., equations) or logical if-then statements to specify how a dynamic system changes from one time point to the next (Harrison, Lin, Carroll, & Carley, 2007; Vancouver, Tamanini, & Yoder, 2010; Vancouver, Weinhardt, & Schmidt, 2010). The advantage of computational models is that they can easily incorporate a large number of process mechanisms that may simultaneously affect system behavior (Goldstone & Gureckis, 2009), making it possible to examine a greater range of possible parameter values than in traditional experimental designs. Weinhardt and Vancouver (2012) provide an excellent overview on the many potential uses of computational modeling in psychology at the individual level. Our interest is harnessing that power to model multilevel emergence and other dynamic phenomena in teams.

The agent-based simulation of bird flocking behavior by Reynolds (1987) is a compelling example of how a concise set of simple process mechanisms and parameters can effectively emulate complex, system level behavior that emerges from the dynamic interactions of individual computational agents, in this case – BOIDS. As we have described previously (Kozlowski & Chao, 2012b; Kozlowski et al., 2013), the boid agents are programmed to optimize three basic rules. These rules are analogous to the process model mechanisms we outlined previously and, in essence, provide the blueprint for the computational model. First, the separation rule specifies that boids should move away from other agents to minimize collisions. Second, the alignment rule specifies that boids should move in the average direction of other

agents. Third, the cohesion rule specifies that boids should move to the center of the flock. Boid agents are randomly placed in a computational space, and the simulation runs. As the code for each boid maximizes the rule set – *in dynamic interaction with the other boids* – collective flocking behavior emerges. Flake (1998) added a fourth rule –boids avoid other agents that block the view – that allows the V-formation of a migrating flock to emerge (see Figure 2). This agent-based simulation is a prime example of how complex group behavior emerges dynamically from individuals striving to maximize their goals as they interact with other individuals striving to maximize goals.

<Insert Figure 2 about here>

For our computational simulation, team members are agents, who follow "rules" in the form of process mechanisms and parameters that guide individual agent behavior in dynamic interaction with other agents comprising the team. The mechanisms of the agents are quite basic, with sparse assumptions. The computational model is programmed in the statistical program R because it allows for easy data generation, and because it provides a useful interface to analyze and graph the results of model runs. It was designed to simulate the learning and sharing of information among team members when engaged in problem solving. Agents learn information through repeated exposure to a piece of information. Consistent with the hidden profile structure of the process model, information is either common or unique. Common information is accessible to all agents. Unique information is only available to a single agent. After information is acquired it must be shared with other agents, and they must learn it and acknowledge it, for it to be "externalized" for problem solving.

The simulation has distinct learning and sharing phases that alternate until all relevant information is acquired by all team members. Agents learn (in either phase) through repeated exposure to a piece of information. During learning phases, agents randomly select a piece of available information and are exposed to it for acquisition. It requires multiple exposures for a piece of information to be acquired. The number of required exposures is determined by a parameter that simulates cognitive ability. Smart agents acquire the information with fewer

exposures than less capable agents. Internalization (i.e., learning) of unique information repeats until the end of the learning phase or until all information has been acquired.

During the sharing phase agents randomly select a piece of information they have internalized and share that information with their team members. Because of the information distribution as common and unique, agents can learn common information either by their own learning behavior or via sharing from other agents. However, the only way for unique information to be acquired by other agents is through first learning and then sharing by the agent that has access to the unique information. The simulation terminates when all agents have learned all information.

One purpose for the computational simulation is to provide evidence to support the fidelity of the process model as a representation of macrocognition and the efficacy of the metrics to capture the dynamics of knowledge emergence. This is not "validation" in the sense that the term is commonly applied in OPB for constructs, but it is an analogous inference. Validating the process model and measurement typology necessitates wide variation in rates of learning and knowledge sharing within and across teams. This requires very large sample sizes; larger than is feasible with human experimentation. This is one critical purpose for the computational simulation, which is to create wide variation in rates of knowledge acquisition as a means to demonstrate that the computational model and knowledge metrics capture the theoretically based forms of team knowledge emergence.

To conduct the validation, one *design principle* is to first determine the constructs of interest that will be manipulated and then choose parameter values from the literature to maximize variance on each of those constructs. The primary mechanisms in the simulation that we manipulated were agent learning and sharing rates, as well as the distribution of common and unique information among team members (agents). These factors were selected for theoretical reasons. Learning and sharing are the primary process mechanisms in the theory of macrocognition (Fiore et al., 2010). Learning rates drive internalization processes and sharing rates drive externalization processes. Thus, they are relevant manipulation targets for creating

variability that the emergence metrics should track. The proportion of common to unique information is also relevant, because it affects the extent to which an agent can learn on its own (i.e., common plus unique information) relative to information that can only be acquired from other agents (i.e., information unique to other agents). The greater the proportion of common information, the more emphasis there is on internalization processes; whereas the greater the proportion of unique information, the more emphasis there is on sharing and externalization.

With the constructs chosen and appropriate parameter values selected, dynamic data for each cell in the design can be generated through the computational model. Due to the ability of computational models to handle large amounts of data, a complex factorial design with large samples for each cell can be easily created; a process that would be nearly impossible to replicate using human experimentation. Once the data have been generated, statistical analyses should be run to determine the sensitivity of the metrics to the manipulations; metrics should behave in theoretically predictable ways. If not, it suggests that the metrics are insensitive to the effects of inputs that should shape emergence and / or the process model does not have fidelity as a representation of emergence for the phenomenon in question. If so, the experiment provides evidence in support for the conceptual synthesis, process mechanisms, and metrics. In addition, it is useful to consider the fidelity of the behavioral results from agent-based modeling with human results in the same problem context. This is consistent with Epstein's (1999) concept of "generative sufficiency," that "Agent-based models provide computational demonstrations that a given micro specification is in fact *sufficient to demonstrate* a macrostructure of interest" (p. 42). This is akin to comparing the fidelity of boid behavior to bird flocking. Such a comparison does not validate the process mechanisms per se. However, it does provide evidence that the computational rules are good candidates for explanation.

An important pragmatic *design principle* is that, depending on the complexity of the virtual experimental design, running an agent-based simulation may be very time consuming using a standard computer or workstation. If possible, utilizing a multi-core computing system that can simultaneously generate data in multiple cells of the design will significantly speed up

the process. For example, in our simulation research, the difference between running the simulation on three computer workstations simultaneously versus using a high performance computing center was a difference of over ten days compared to three hours, respectively, of computing time.

Design and develop a human-based synthetic world. Synthetic tasks are used as training environments when the consequences of trainee errors can be catastrophic (e.g., aviation, medicine, nuclear power control, etc.). They are also used in research to provide a more middle ground between pure laboratory and field research methods (Runkel & McGrath, 1972). There are well established procedures for developing synthetic worlds (Schiflett, Elliott, Salas, & Coovert, 2004). One *design principle* is that the problem domain needs to be significant but focused. As we highlighted previously, this is substantially influenced by the selection of a middle range theory as the primary substantive focus. This means that the design of the synthetic world is problem focused, with less attention devoted to physical fidelity beyond what is necessary to frame the problem. Contextual factors, as antecedents or moderators, are generally treated as manipulations in a synthetic world. A related *design principle* is to ensure that the synthetic task has psychological fidelity with respect to the phenomena of interest. Kozlowski and DeShon (2004) define psychological fidelity as ensuring that the synthetic world entails the core constructs, psychological processes, and behavioral actions relevant to the phenomena of interest. Given the previous steps for paradigm development we have discussed, these aspects are explicit.

We constructed a human-based synthetic task that emulates the structure of macrocognitive problem solving: iterative knowledge acquisition, individual to team knowledge emergence, and effects on decision effectiveness examined over time. The synthetic task can be used to evaluate the diagnostic value of the metrics and their utility to drive experimental interventions designed to enhance team macrocognition and knowledge emergence. A key feature of the simulation is that knowledge acquisition, knowledge sharing, and the pool of knowledge available to the team for decision making is collected via individual behavior as team

members search for information, acquire it, and share it with their teammates; no self-reports are required. However, self-reported perceptions and reactions (e.g., shared mental models, team efficacy, team cohesion) can be collected to assess "team process constructs" or "emergent states" (Marks et al., 2001) beyond macrocognitive processes and outcomes.

<Insert Figure 3 about here>

We designed CRONUS[4] to be linked to the computational process model / measurement typology and the computational simulation. The information distribution structure of the task is based on a hidden profile (Stasser & Titus, 1985), wherein team members have access to common information and also information unique to their role. Both unique and common information have to be acquired, shared, and utilized for team members to be able to make an optimal decision. A robust finding of hidden profile research is that team members share common information but do not share all their relevant unique information, leading to suboptimal decisions (Stasser, 1999). Although hidden profile research typically relies on a team making a single decision, we designed our simulation to incorporate a series of problem scenarios. This enables us to model learning that transfers across scenarios. Thus, we can use the metrics to capture knowledge emergence within scenarios, model knowledge emergence processes across multiple scenarios, and track trajectories of decision improvement with experience. This allows a much more sensitive evaluation of interventions and their ability to enhance team learning and decision effectiveness over time. CRONUS is scalable (i.e., problem space, team size) for investigators who may be interested in more in-depth, within scenario studies. We have collected exemplar data to demonstrate fidelity (i.e., generative sufficiency) between the knowledge emergence metrics generated by process model / agent-based simulation and knowledge emergence in human teams. These comparisons are addressed in our discussion section.

Data analytic considerations. A good theory and associated research paradigm are only as informative as data analytic techniques allow them to be. As such, it is necessary to utilize

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[4] CRONUS is an acronym for Crisis Relief Operation: Naval Unit Simulation. Cronus is also the Titan god of time in Greek mythology.

appropriate statistical tools to answer the research questions of interest. Advancing the computational, agent-based simulation enables a mapping of the theoretical framework to a formal model (Harrison, Lin, Carroll, & Carley, 2007). Further, by utilizing human data to better inform simulation parameters, researchers will be able to model the dynamics of the process model accurately over larger samples and longer time points than is possible in a laboratory paradigm. Moreover, using traditional growth curve modeling to analyze the data allows for validation of the measurement typology and also provides insights into how teams differ in their rates of knowledge acquisition and sharing along with how those rates relate to effective team decision making. Finally, the theory of macrocognition (Fiore et al., 2010) proposes a multiphase process of team learning that cannot be fully captured with statistical methods (e.g., multilevel random coefficient modeling; MRCM) typically employed in organizational science. Therefore, vector auto-regressive (VAR) models can be applied to determine how behavior in one phase of the macrocognitive process relates to behavior in subsequent phases (DeShon, 2012).

The synthetic task tracks individual and team behaviors within and between problem scenarios or "trials." Within a trial, CRONUS tracks when individuals learn and share particular pieces of information, either unique or common, with teammates. This allows for an examination of individual and team learning rates during each trial, and at the same time, allows for a comparison of individual and team learning rates between trials. Therefore, we may examine the relative effectiveness and efficiency of each individual and the team as a whole.

The tracking of individual behaviors over time, both within and between trials, necessitates longitudinal data analysis. A *design principle* in the selection of a data analytic approach centers on the research focus. A focus on the improvement or growth of the phenomenon over a series of trials necessitates longitudinal growth curve modeling, whereas a focus on reciprocal dynamics is better suited for analysis by VAR modeling. MRCM serves as the most common approach to longitudinal data analysis in the organizational sciences. Given the interest in team behaviors, a three-level (intra-individual, inter-individual, and inter-team)

MRCM model captures the individual dynamics of team members, while at the same time accounting for differences between individuals and teams. Such models provide a platform to examine multilevel influences; that is, how the behaviors of individuals change over time and the extent to which changes in behavior result from intra-individual processes or inter-individual and team differences (Raudenbush & Bryk, 2002; Singer & Willet, 2003). MRCM is particularly useful because it can provide accurate estimates of relationships for even relatively few time periods (T < 5). Additionally, statistical software (e.g., SPSS, HLM) is readily available for organizational researchers that allow them to easily analyze data for any number of individuals, teams, and time points.

However, despite the prevalence of MRCM in the organizational sciences, it is limited to understanding relationships among several predictors and a single dependent variable. With a paradigm focused on emergence dynamics, it is very useful to capture collaboration in a way that estimates how teammates impact one another. VAR serves this purpose better. VAR treats each variable symmetrically by explaining the trajectory of each variable by its own lag (i.e., prior realizations) and the lag of the other variables in the model. In a VAR model, evolution of each variable over a sample time period equals a linear function of the past evolution of all the variables in the model (Enders, 1995). Thus, VAR proves particularly useful when we conceive of the variables in the model as functions of each other (i.e., each variable is treated as an endogenous variable). For example, in team macrocognition all individuals in a team are simultaneously learning and sharing information. Examining lagged relationships of how teammates impact each other's learning and sharing processes is vital to understanding collaboration; that is, to examine the process mechanisms of emergence dynamics. A VAR analysis allows us to capture these collaboration dynamics in ways that more common approaches like MRCM do not.

Unfortunately, all statistical methods have limitations and VAR is no exception. First, although VAR is readily equipped to model reciprocal dynamics at the lower level that are the process mechanisms of emergent phenomena, it does not cut across levels as does MRCM.

That is, VAR does not aggregate lower level observations to represent higher level constructs (i.e., a "team process" or "emergent state" construct). Rather, VAR enables a focus on the process dynamics of emergence. Second, to properly run a VAR model and get convergence, it is necessary to have relatively long streams of data (T > 20) for each individual. This is entirely tractable with the hybrid approach combining computational modeling and human task simulation that we advance, although it can be a challenge for more conventional research methods. Finally, many of the statistical software packages commonly used by organizational researchers (e.g., SPSS, M-PLUS, HLM) do not offer VAR estimation. As a result, researchers will have to familiarize themselves with alternative syntax-driven software platforms such as SAS, Matlab, or R.

Conduct systematic research and advance the paradigm. Team research is resource intensive. It takes X participants (fill in the size of your teams) to generate one data point. Add in a focus on emergence, where the frequency of assessment has to be commensurate with the rate of meaningful process dynamics, and you have a very demanding research design for data collection. How can one maximize the effectiveness and information value of such research?

An innovative feature of our research approach is that we plan to incrementally integrate human behavior parameters and processes into the agent based simulation. This is a *design principle* in the coupling of theory (substantive and multilevel), emergence processes and metrics, computational simulation, and human experimentation. That is, we will use results from human research using CRONUS to add precision to the computational model parameter values, refine the emergence process mechanisms, and elaborate the mechanisms (i.e., add additional mechanisms, increment complexity) underlying the agent-based simulation. This will allow us to improve the precision of the dynamic process model and the agent-based simulation.

Another *design principle* is that as the computational agents advance in complexity and improve in fidelity, we can use the agent-based simulation to conduct virtual experiments. That is, the agent-based simulation can be used as an experimental platform to synthetically explore possible intervention points designed to enhance macrocognitive processes and knowledge

emergence. Promising interventions can then be evaluated using human research to verify effects. Such an approach enhances efficiency for research that is inherently inefficient. For example, theory suggests that factors internal to the team that represent individual differences (e.g., cognitive ability, propensity to communicate) and external to the team that represent contextual factors (e.g., communication protocols, leadership) are likely to influence emergence dynamics. Thus, given a validated agent-based intervention, internal and external factors can be investigated as "manipulations" in virtual experiments. So long as theory can guide the hypothesized effects of the internal and external contextual factors on the process mechanisms, one can posit hypotheses that can fully explore the theoretical space. Promising results can then be verified with targeted human experimentation.

There are three core elements needed to implement this approach: fidelity, theory, and data. First, one needs evidence for the fidelity or comparability between the dynamic process model / computational model and human behavior. This provides an indication that the primary theoretical processes are plausible explanations for analogous human behavior. Note that we are not asserting that fidelity means that the theoretical processes account for actual behavior, only that they are a plausible point of departure. No one is asserting that real birds are behaving according to boid computational rules; we merely infer that the rule set yields a reasonable emulation of the emergence of flocking behavior (and also herding in animals and schooling in fish). Second, one needs theory as a basis for identifying additional refinements to the process mechanisms (or additional processes as well). In its current iteration, the dynamic process model is very basic with only two primary process mechanisms: learning and sharing. Learning rates are a function of a parameter that essentially represents cognitive ability. Sharing rates are a function of a parameter that represents extroversion. However, sharing one's knowledge in a group may be influenced by other individual and group characteristics as well. For example, one's self-esteem (Rosenberg, 1989), individual sense of collectivism (Jackson, Colquitt, Wesson, & Zapata-Phelan, 2006) and one's status in the group (Thomas-Hunt, Ogden, & Neale, 2003) are likely to influence the propensity to share. External factors, like leadership or

communication protocols, represent contextual factors that are also likely to influence sharing and can be implemented virtually. Parameters to represent the influence of these factors can be added to the process model and agent code. Third, one needs human data to generate appropriate parameter values. Initially, parameter values are specified based on estimates drawn from the literature. Because CRONUS was designed in parallel with our theoretical foundation, metrics, and computational model, results from human experimentation can be used to add precision to the parameter values. With this integrative approach, over time the process / computational model and human behavior should converge to a point where computational simulation will be nearly as informative as human research (so long as the process mechanisms are core to the phenomenon of interest).

Initial research indicates very good fidelity between the behavior of agent-based teams, based on the process model and computational simulation, and human teams performing CRONUS. Figure 4 presents data from four team learning trials; the data in Panels A and C were generated using simulated agent teams ('droids') while Panels B and D show data from human teams (human 'noids'). The graphs display change in the proportion of total pieces of information learned from a given pool of information by each individual in a three member team over time. Although these observations present only a single metric for depicting knowledge emergence in teams, their comparison illustrates a number of compelling similarities between the specification of the formal computational model and the behaviors exhibited by human teams. As emphasized by the vertical dividing line overlaid on each graph, two relatively distinctive emergent "phases" are observable in both agent and human teams dictated by the primary activities undertaken by members during those periods of time. Consistent with the theory of macrocognition (Fiore et al., 2010), both agent and human team members initially engage in an activity phase during which individual, self-controlled *learning* dominates (i.e., internalization: team members focus on acquiring information to which each member has unique access) followed by a more interactive, team-oriented *sharing* phase (i.e., externalization: team focus shifts to communicating relevant information to other team members, learning information

shared by others, and ensuring that all members have learned the relevant information).

Furthermore and as expected, differences in an individual's ability to learn from direct versus

indirect exposure to information and the added complexity of organizing and communicating

unique information between individuals led to substantially longer sharing phases relative to the

comparatively short learning phases in both agent and human teams.

<Insert Figure 4 about here>

These findings illustrate that, even with a very sparse process model, the agent-based

simulation exhibits fidelity with commensurate human teams performing CRONUS. However, of

greater interest is the potential for the agent-based model and accompanying metrics of

emergence to serve as tools for identifying and evaluating points of leverage for improving team

effectiveness. For example, data from the computationally driven agent teams shown in Panels

A and C in Figure 4 suggest that when learning rates exhibit greater variance across members,

longer periods of stagnation in team learning activities occurs. Panel A shows an agent team

composed of a "fast" learner (i.e., an agent completes the learning phase more quickly than the

other agents), a "slow" learner, and a learner somewhere in between. Alternatively, Panel C

provides an example of a team in which learners are relatively similar in their capabilities. An

examination of learning outcomes during Team A's sharing phase reveals relatively long periods

of stagnation (represented by flat horizontal lines) in learning during which no new information is

being learned by any team member. This bottleneck in team learning manifests as the slowest

team member not only takes longer to learn information, but other team members are forced to

direct more of their resources towards helping the slower members (i.e., the faster members

have to spend more time communicating information to ensure that the slower members have

learned it), thereby inhibiting the faster members from directing their attention towards learning

new information as well. By comparison, the homogenous learning rates of Team C's members

contribute to a more stable and gradual increase in team learning during the sharing phase with

fewer extended periods of idleness. Similar patterns were borne out in human teams as well;

the diversity of learning rates in Team B's members contributed to longer periods of stagnation

(especially for the fast learner) when compared to the relatively stable rates of learning exhibited by Team D (whose members exhibited less variance in learning rates) during the sharing phase.

Such data and patterns of emergence are diagnostic of team inefficiencies and are useful for identifying possible interventions to improve team learning activities. In the example above, real-time feedback or monitoring tools can be implemented to encourage temporal synchronicity in team learning activities. Alternatively, team training that focuses on the development of effective communication strategies, leadership, and team back-up behaviors (e.g., Marks et al., 2001) could be introduced which encourage team members to adapt their sharing activities when one or more members feel overloaded and unable to keep pace. These contextual interventions can be examined virtually to map effects and to fine tune their implementation. In the long term, as the process and linked computational models continue to gain complexity and precision, we will have the capability to develop agent-based, synthetic teammates to interact with humans in research using CRONUS. That is, as we more precisely isolate key factors that influence learning and sharing processes, and more accurately parameterize their values, we will be able to compose specific team profiles by building teams based on target attributes of human actors – supplemented by agent-based teammates – so we can examine ways to enhance collaborative learning and knowledge emergence in teams.

Discussion

Contributions

Our point of departure for this paper emphasized that there are two fundamental systems processes in organizations – top-down, contextual effects and bottom-up emergent phenomena; that multilevel research in organizational science is overwhelmingly focused on cross-level contextual effects; and that when emergence is considered it is assumed theoretically, assessed statically, and treated in limited forms. We have asserted that understanding emergence theoretically and developing research capabilities to model it as a dynamical process are foundational for advancing multilevel research in organizational science.

That is the target of our paradigm; it integrates substantive and multilevel theory, emergence-based metrics, agent-based simulation, and human synthetic task research.

Where does our approach fit in the big picture? The target of our paradigm – emergence as a dynamic process – is very little explored in OPB and its understanding is essential for advancing multilevel theory. Organizational science is a very broad scholarly endeavor that is comprised of different academic disciplines, target levels, assumptions, and methods. From a meta-theoretical perspective, one can view the treatment of emergence in organizational science in a framework with two orthogonal dimensions (Kozlowski & Chao, 2012b): Investigation (indirect or direct) and Methodology (qualitative or quantitative). Indirect investigations assume emergence theoretically but do not assess it, whereas direct investigations involve data collection that can capture emergence as a process. Qualitative studies tend to be case-based, richly descriptive, and holistic in the interpretation of emergence as a process, but challenged with respect to replication and generalization. Quantitative studies entail multiple observations, with a focus on measurement precision, replication, and generalization, so the process aspects of emergence – so far - are often highly constrained.

This meta-theoretical framework yields four quadrants. Quadrant 1 – qualitative-indirect – is represented by retrospective accounts from interviews, narratives, or case studies (e.g., Stewart, 2005). Quadrant 2 – qualitative-direct – is represented by participant observation and participatory action research (e.g., Kemmis & McTaggart, 2005). As we have argued, quadrant 3 – quantitative-indirect – is the home of most multilevel research that implicates emergence in OPB. Quadrant 4 – quantitative-direct – is largely dominated by computational, agent-based simulation research (e.g., Miller & Page, 2007). The purpose of our paradigm is to push more micro-meso OPB research on emergence from quadrant 3 into quadrant 4; to supplement and add precision to agent-based modeling by incorporating research using human actors; and to integrate these approaches as a way to advance theory, measurement, and research methodology for studying multilevel emergence in OPB. If that is to happen, investigators will need to develop appropriate research paradigms that can elucidate emergence for their

phenomena of interest. We have provided a conceptual architecture and design principles for developing a hybrid paradigm that couples computational modeling and human experimentation, and illustrated their application with our research focus as an exemplar. Our hope is that other investigators will use this "how to" guidance and will extend the approach to study other emergent phenomena in teams. Kozlowski et al. (2013) explicate some promising emergent team process targets for such research advances.

We believe that this approach to studying emergence and team process dynamics directly is an important contribution to enlarging the research design arsenal for organizational science. Team processes, as dynamic phenomena rather than as static constructs or emergent states, have been largely neglected in team research (Cronin et al., 2011). Computational modeling, particularly when coupled with traditional correlational and experimental designs, enlarges the methodological toolbox (Hulin & Ilgen, 2000). Our approach offers one means of initiating more research that is process centric so organization science can begin to probe this knowledge frontier.

That point is critical. We advocate for *supplementing* traditional correlational and experimental methods with computational modeling and virtual experimentation; we are not arguing to *supplant* existing methods. There are many basic theoretical questions that can legitimately be addressed using the dominant approaches and they will continue to be used. What we offer promises innovative insights into the basic process mechanisms and the dynamics of emergence.

Strengths and Limitations

Our paradigm for studying emergence is innovative and incorporates several strengths, but of course it also has off-setting limitations. The primary issues parallel the well-trod distinction between lab- and field-based research. Simulation occupies a "middle ground" to some extent (Runkel & McGrath, 1972), but it clearly is more lab-like than field-like. The strengths of our approach center on precision in theory, measurement, modeling, and experimentation. The inferences that can be drawn will be strong. Limitations include

constraining assumptions, domain specificity (to some extent), limited time frames for

investigation (at least for human actors), and limited contexts. Obviously, to seriously advance

research in quadrant 4, our paradigm will need to be supplemented by other quantitative-direct

approaches which hone in on phenomena of interest using alternative synthetic tasks and,

importantly, that get out of the lab and into the "wild" to measure human interaction in natural

contexts with high frequency sampling over lengthy periods of time.

Generalization

Our paradigm was purpose-built to study collaborative learning and knowledge

emergence in teams, so one appropriate question concerns how useful it is for informing

research on emergence outside of that specific domain. *At a molar level, what we have*

developed is an architecture for "how to" build a research paradigm to study emergence

dynamics in teams. As with any research design method, it is highly flexible within its

boundaries. Thus, the general architecture shown in Figure 1 is highly generalizable to

emergent phenomena that can be modeled computationally and studied using synthetic tasks.

Kozlowski et al. (2013) highlight three emergent phenomena in teams for which this approach

holds particular promise, and others are easy to identify.

At the more specific level of the team knowledge research paradigm, generalization is by

necessity more constrained but still highly applicable. As we noted previously, the fundamental

emergence process at the focus of this paradigm is based on additive elemental content and the

process is targeted at the micro-meso levels. Thus, the paradigm – in terms of the metrics,

process mechanisms, and computational modeling – can be readily adapted or generalized to

other emergent phenomena that fit these assumptions. For example, over the last decade a

consensus has developed in the literature (LePine, Piccolo, Jackson, Mathieu, & Saul, 2008)

around the behavioral process taxonomy posed by Marks et al. (2001). That taxonomy

integrated and organized extant research on team behavioral processes structured around a

temporal distinction between transition processes – where teams prepare for task engagements

(e.g., set goals, strategize) or reflect on their performance post-engagement – and action

processes when teams coordinate, correct errors, and back each other up. There are also

interpersonal processes (e.g., conflict management) that are always relevant. Basic research

that focuses on behavioral processes in the military, aviation, and medical communities typically

uses simulation to prompt behavioral processes and observational checklists to assess them

(e.g., Fernandez, Kozlowski, Shapiro, & Salas, 2008). Thus, team behavioral processes can be

captured as an additive emergence process, and the patterns by which they emerge exhibits a

range of forms similar to knowledge emergence.

With respect to generalizing our paradigm to focus on behavioral processes, the same

steps would apply, but the approach would have to adapt to the specifics of the domain. For

example, substantive theory would change and thus the underlying elemental content, forms of

emergence, and process mechanisms would have to be specified for action team behavioral

processes. The dimensions of the team process taxonomy identify the domain, but the

elemental content would have to be specified for the task in question. For example, researchers

examining team processes in medicine often use a high-fidelity patient simulator and video to

record teams in action. Team processes are operationalized by specific behaviors exhibited

during a scenario that link to behavioral process dimensions (e.g., Grand, Pearce, Rench, Chao,

Fernandez, & Kozlowski, 2013). The metrics would generalize, but their meaning would change

to fit the domain; one would need to specify the interaction "rules." That is, the metrics would

have new meaning linked to the processes of emergence and the forms it would take for

different behavioral processes. If one were interested in developing a paradigm that modeled

other types of emergent phenomena, the design principles would apply but the focal process

mechanisms, metrics, and computational model would necessitate greater modification.

Research paradigms are specific to a target domain. The approach, however, is highly

generalizable to a wide range of emergent phenomena in teams.

Conclusion

Scholars have highlighted that the evolution of multilevel theory and research methods

from the periphery of organizational behavior research to its core represents a major advance in

the sophistication of quantitative organizational science (Kozlowski, 2012b; Mathieu & Chen, 2011). Multilevel research is helping us bridge levels of the organizational system that were heretofore studied in isolation, investigate much more complex and nuanced organizational phenomena, and gain a more articulated understanding of social-organizational systems. This is all good. At the same time, however, theory and research have to some extent fallen into a well-trodden rut. It is a rut composed of cross-level research focused primarily on composition-based constructs that are assumed to have emerged from lower levels of the system (Kozlowski & Chao, 2012b). We assert that the next phase of advancement has to center on emergence as a dynamic process. Theory, research, and methods have to focus on the nature, fundamental processes, and dynamics of emergence. We have to develop methods to map its varieties, track its dynamics, and model it. This paradigm based on an integration of theory, measurement, agent-based simulation, and human-based simulation is one way to get us started on the next phase of evolution for multilevel theory and research, and the investigation of team process dynamics.

Endnote: Glossary of Key Terms

Emergent constructs – Composition (or compilation) based aggregations of individual level assessments that originate in individual cognition, affect, or behavior and that are used to represent a collective concept for purposes of analysis, model-testing, and inference. The construct validity of composition constructs is based on assumptions that human interaction yields convergence in perceptions, affect, or behavior as people share their views and feelings over time. This convergence assumption is generally substantiated with evidence for restricted within group variance (Bliese, 2000; Kozlowski & Klein, 2000). Representation standards are not well established for compilation constructs. Note that convergence over time is not directly observed and stability of the emerged form is also typically an assumption (Kozlowski & Chao, 2012b). This is the most common way in which emergence is studied in OBP.

Emergent phenomena – As defined by Kozlowski and Klein (2000), dynamic interaction and exchanges among individuals, originating in their psychological characteristics (e.g., cognitive, affective, or behavioral), and within organizational units (e.g., group, team, work system) can enact bottom-up, emergent phenomena that manifest collectively over time. Emergent phenomena are process-centric and, although they *may* exhibit stability and appear to be construct-like, they are fundamentally grounded in the elemental content and process mechanisms that drive human interaction and exchange. We prefer to label process mechanisms and collective manifestations "emergent phenomena" rather than emergent constructs. Emergent phenomena as dynamic processes are rarely studied directly.

Emergent states – This term was coined by Marks et al. (2001) to distinguish the direct observation and assessment of team behaviors which reference "teamwork processes" (that were the focus of their team process taxonomy) from the more common treatment in the extant literature of "team processes" based on aggregated assessments of individual responses to survey items targeting cognitive, affective, or behavioral perceptions. They labeled such assessments "emergent states." Emergent states are conceptually and operationally equivalent to an assessment of team process foci as "emergent constructs."

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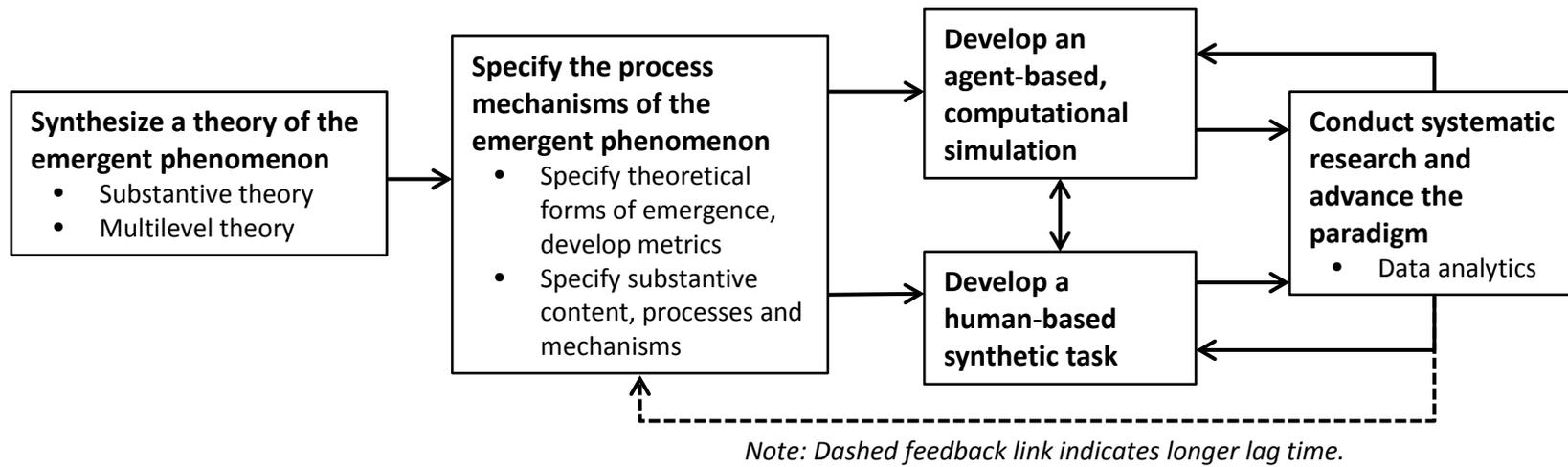
Table 1. Steps and design principles for paradigm development.

Steps	Design Principles
Synthesize a theory of the emergent phenomenon of interest (substantive and multilevel theory)	• Ensure the substantive theoretical focus fits the temporal frame/context of the research approach • Ensure theory articulates basic elemental content (i.e., what lowest level units do) and process mechanisms (i.e., how lowest level units do it) which describe dynamics in the substantive phenomenon
Specify the theoretical forms of emergence and develop metrics to capture them	• Define and differentiate the forms of emergence relevant to the substantive phenomenon (e.g., composition, compilation, etc.) • Pursue alternate forms of emergence in the substantive domain; if necessary, explicate how/when different patterns of emergence manifest • Metrics need to capture rate of emergence; should be targeted at lowest level unit of interest and collected at a rate commensurate with the pace of emergence
Specify the substantive content, processes and mechanisms	• Specify and conceptually define the focal substance of the theory, i.e., the elemental content (e.g., attitudes, cognitions, behaviors, etc.) which collectively contribute to emergence • Explicate the mechanisms of emergence as a process model which describes how elemental content interacts to produce patterns of emergence • Incorporate where variation in emergent patterns/outcomes may arise in the process model • Link metrics to process model

Develop an agent-based, computational simulation	• Formally (i.e., mathematically) specify the iterative relations/interactions among elemental content which represent the process mechanisms of emergence
	• Construct simulation output in manner consistent with metrics
	• Validating computational simulation:
	   o Choose parameter values for relevant constructs of interest that maximize variance
	   o Use computer systems with adequate processing power

Design and develop a human-based synthetic world	• Select a middle range problem domain in which contextual factors can be controlled • Ensure high degree of psychological fidelity
Data analytic considerations	• Allow substantive focus of the research question and nature of the emergent interactions to guide selection of data analytic approach

Conduct systematic research and advance the paradigm	• Integrate new parameter estimates based on human data into computational simulation
	• As precision/fidelity of simulation improve, explore intervention possibilities using computational simulation and validate findings with human data
	• Core elements of systematic research approach:
	   o *Fidelity*: Evaluate comparability between process model, computational model, and human behavior
	   o *Theory*: Support refinements to models with substantive theory
	   o *Data*: Allow human data to influence simulation parameters

Table 2. Knowledge typology metrics.

Knowledge Typology Metric	Level of Measurement	Metric Type	Description	Example: 3-person new product development team: A = market researcher, B = design engineer, C = production manager
Individual knowledge	Individual	Discrete	The amount of knowledge an individual has, relevant to a total knowledge pool. How much does an individual know?	At team inception, A has extensive knowledge of consumer preferences and understands new product process; B is familiar with innovative product features and with product design; C is new to product innovation and unfamiliar with the organizational process.
Knowledge pool	Team	Discrete	The amount of knowledge a team has, relevant to a total knowledge pool. How much does the team know?	At team inception, the knowledge pool is extensive on consumer preferences, moderate on innovation, and light on managerial production processes.
Knowledge configuration – Internalized and externalized	Multilevel: • Individual • Dyadic • Team	Discrete	The pattern of the knowledge pool across team members – what knowledge is uniquely held by one individual, and what knowledge is shared among two or more team members. Who knows what?	At team inception, A's knowledge of consumer preferences is unique – B and C have not learned what A knows. A and B share common knowledge of product innovations, but B's knowledge is more technical in some areas than A's.
Knowledge acquisition	Individual	Dynamic	Over time, an individual's learning rate in acquiring new knowledge. How fast does an individual learn?	At first, C learns quickly from A about consumer preferences. Later, C has trouble understanding technical innovations and the learning rate slows down.
Knowledge variability – Internalized and externalized	Team	Dynamic	The variance of different rates of knowledge acquisition within a team. What are the differences in learning rates across team members?	A learns quickly from B about technical innovations but C has trouble understanding technical information and learns slowly from B.
Knowledge emergence within team	Team	Dynamic	Rates of growth for knowledge pool and knowledge configuration within a team. How fast does a team learn and who knows what over time?	The rate of growth for knowledge on consumer preferences is fast and A's unique knowledge quickly becomes common knowledge to B and C. Some of B's technical knowledge continues to be unique knowledge that only B knows.
Knowledge emergence between teams	Team	Dynamic	Rates of growth for knowledge pool, knowledge configuration, and knowledge variability across teams. How do teams compare in knowledge emergence?	The emergence of new knowledge in this team is slower than a team that has extensive initial individual knowledge; where everyone learns quickly, and more knowledge is common to the team, instead of unique to one member.

Figure 1. General Architecture for the Development of a Research Paradigm with an Example for Studying Team Knowledge Emergence

Synthesize a theory of the emergent phenomenon
- Substantive theory
- Multilevel theory

Specify the process mechanisms of the emergent phenomenon
- Specify theoretical forms of emergence, develop metrics
- Specify substantive content, processes and mechanisms

Develop an agent-based, computational simulation

Develop a human-based synthetic task

Conduct systematic research and advance the paradigm
- Data analytics

Note: Dashed feedback link indicates longer lag time.

Example for Studying Team Knowledge Emergence

The theory of macrocognition is a conceptualization of team learning that is multilevel, dynamic, and emergent in nature. It is synthesized with principles of multilevel theory

- Knowledge emergence focuses on learning and knowledge sharing. Metrics described in Table 2.
- Forms of emergence begin in a compilation configuration as individuals learn unique information and transition to a composition configuration as information is shared and externalized into common team knowledge.

Computational simulations can vary agent learning rates, sharing rates, and the distribution of common and unique information.

CRONUS involves 3-person teams in a series of decision making scenarios. Each person has access to unique and common information.

The synthetic task is used to compare the behavior of human teams to agent teams. Agent-based simulations can identify leverage points that can influence phenomena of interest for study in human teams.
- Vector auto-regressive models determine how behavior in one macrocognitive phase relates to behavior in subsequent phases.
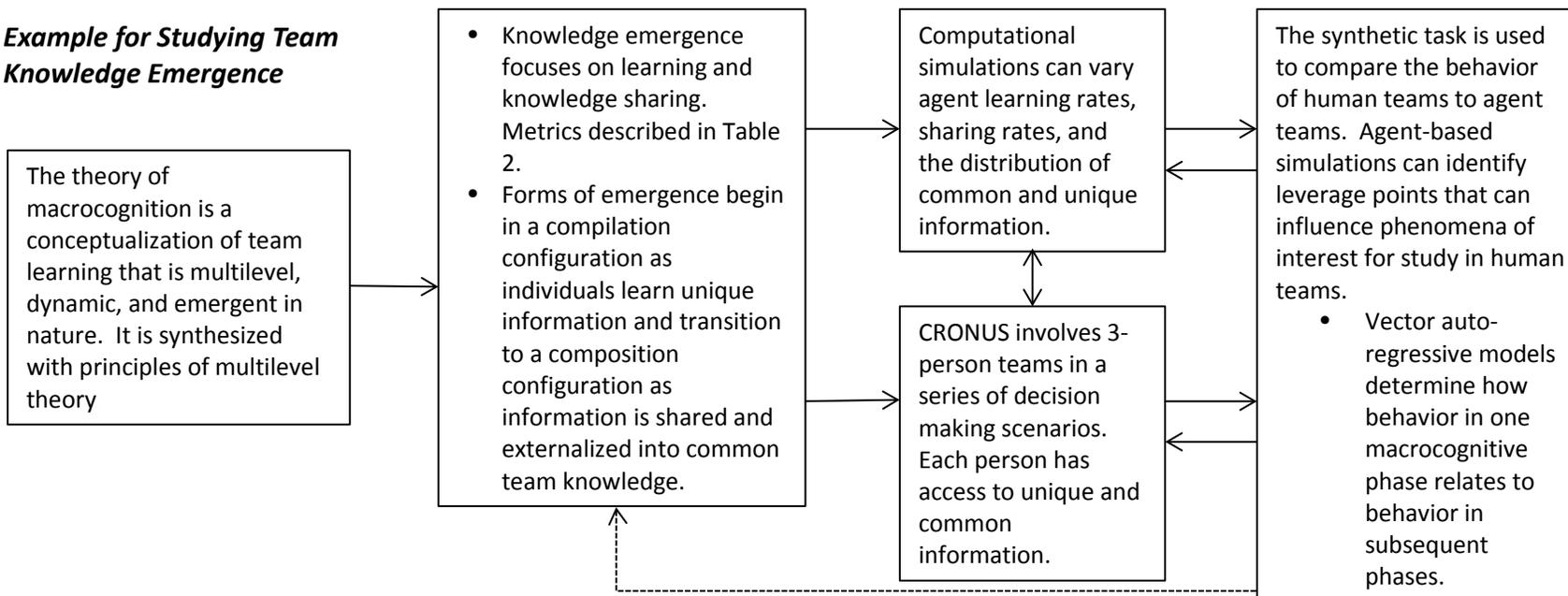
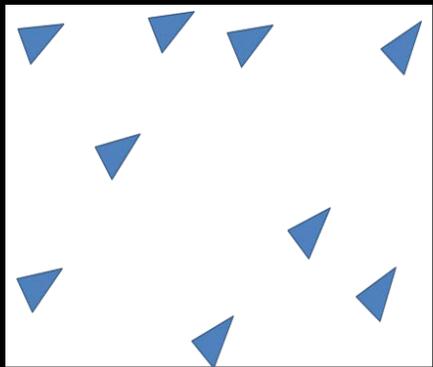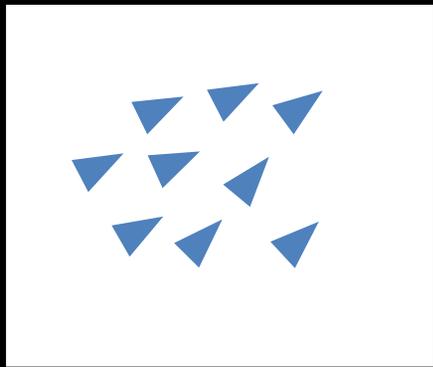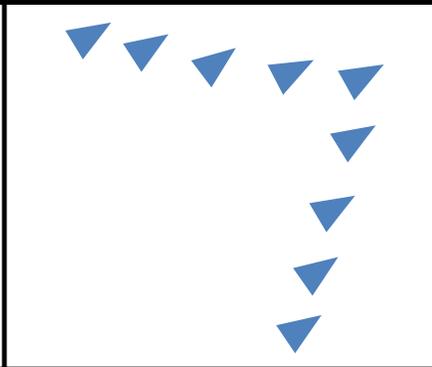Figure 2. Agent-based, Computational Simulation – BOID Rules

Rule 1: Separation – boids move away from other boids to avoid collisions.	Rule 2: Alignment – boids move in average direction and speed of other boids.	Rule 3: Cohesion – boids move to center of flock to avoid predators.	Rule 4: View – boids maintain a clear view ahead and move to avoid boids blocking the view.
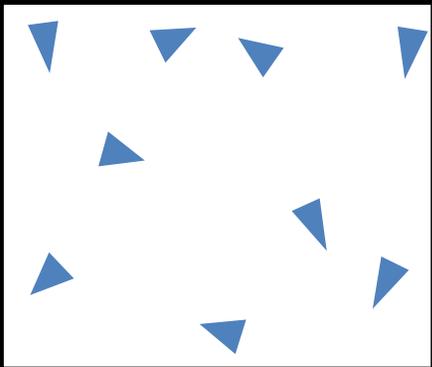
Figure 3. CRONUS Architecture.

_Summary__: Group planning & decision-making task that requires members to acquire knowledge & integrate distributed expertise into a single problem solution_

➢ **Performance:** Group decision based on *individual* learning & sharing and *team* integration of distributed knowledge

  ▪ Optimal solutions require the relevant knowledge of all members to be leveraged

  ▪ Deviations from optimality occur when relevant knowledge is not incorporated into the team decision
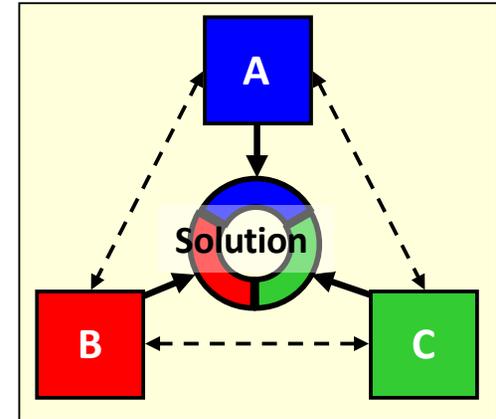
➢ **Design:** Multiple, self-contained scenarios requiring a series of unique decisions within the context of a larger mission

  ▪ Allows <u>longitudinal</u> examination of individual and team knowledge building processes, knowledge emergence, & products as defined by the TKT, as well as <u>performance trajectories</u> across the mission space
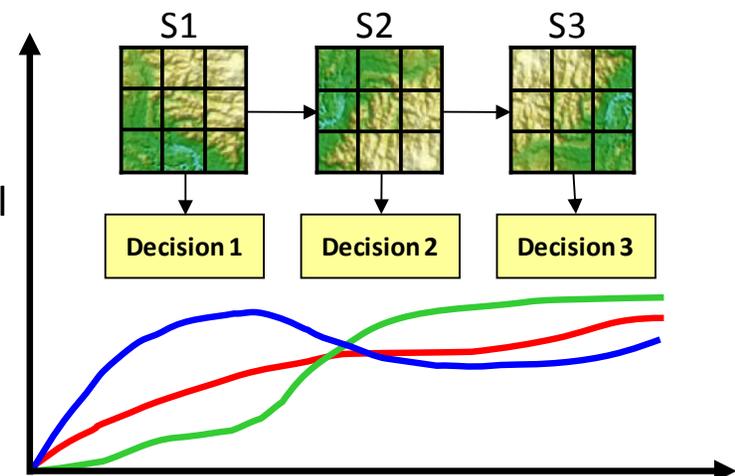
Figure 4. Comparison of information acquisition rates by team members in agent and human teams.